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CAR MAKE AND MODEL RECOGNITION UNDER LIMITED LIGHTING CONDITIONS AT NIGHT

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by

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ABSTRACT

Car make and model recognition (CMMR) has become an important part of intelligent transport systems. Information provided by CMMR can be utilized when licence plate numbers cannot be identified or fake number plates are used. CMMR can also be used when automatic identification of a certain model of a vehicle by camera is required. The majority of existing CMMR methods are designed to be used only in daytime when most car features can be easily seen. Few methods have been developed to cope with limited lighting conditions at night where many vehicle features cannot be detected. This work identifies car make and model at night by using available rear view features. A binary classifier ensemble is presented, designed to identify a particular car model of interest from other models. The combination of salient geographical and shape features of taillights and licence plates from the rear view are extracted and used in the recognition process. The majority vote of individual classifiers, support vector machine, decision tree, and k-nearest neighbours is applied to verify a target model in the classification process. The experiments on 100 car makes and models captured under limited lighting conditions at night against about 400 other car models show average high classification accuracy about 93%. The classification accuracy of the presented technique, 93%, is a bit lower than the daytime technique, as reported at 98 % tested on 21 CMMs (Zhang, 2013). However, with the limitation of car appearances at night, the classification accuracy of the car appearances gained from the technique used in this study is satisfied.

DECLARATION

I declare that this thesis is my own unaided work. It's being submitted for the degree of Doctor of Philosophy of University of Bedfordshire.

It has not been submitted before for any degree or examination in any other university.

Name of candidate: MR. NOPPAKUN BOONSIM

Signature:

Date: 03/10/2016

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LIST OF ABBREBVATIONS

ANPR	Automatic Number Plate Recognition
LPR	Licence Plate Recognition
OCR	Optical Character Recognition
CMMR	Car Make and Model Recognition
CCTV	Closed-circuit television
GA	Genetic Algorithm
SVM	Support Vector Machine
DT	Decision Tree
ID3	Iterative Dichotomieser 3
C4.5	Successor of ID3
CART	Classification and Regression Tree
CHAID	Chi-squared Automation Iteration Detector
K-NN	K-Nearest Neighbors
ANN	Artificial Neural Networks
Adaboost	Adaptive Boosting
CV	Cross Validation
RGB	Red Green Blue
YCbCr	Luna Blue-difference Red-difference
L*a*b*	Lightness a and b colour-opponent dimensions
HSV	Hue Saturation Value
CMYK	Cyan Magenta Yellow Black
HE	Histogram Equalization
BHE	Bi Histogram Equalization
DSIHE	Dual Sub-Image Histogram Equalization
SSD	Sum of Square Different
SUSAN	Small Univalue Segment Assimilating Nucleus
TL	Taillight
SIFT	Scale Invariant Feature Transform

SURF	Speed Up Robust Feature
VR	Vehicle Recognition
ITS	Intelligence Transport System
VCR	Vehicle Class Recognition
ROI	Region of Interest
PHOG	Pyramid Histogram of Gradient
LDA	Linear Discriminant Analysis
HOG	Histogram of Gradient
SMG	Square Mapped Gradient
LNHS	Locally Normalized Harris Strengths
RD	Reference Database
QI	Query Image
XML	Extensible Markup Language
SVOOC	Sparse Vector of Occurrence Counts
HL	Headlight
TTC	Time to collision
DAS	Driver Assistance System
SE	Structure Element
CV	Coefficient Variation
CCA	Connected Component Analysis
DS	Distance symmetry Score
AS	Area symmetry Score
ARS	Aspect Ratio symmetry Score
PCA	Principle Component Analysis
PSO	Particle Swam Optimization
RBF	Radial Basis Function
CSV	Comma Separated Values

LIST OF NOTATIONS

Chapter 2

$(x \cdot y+1)^p$	Polynomial kernel
$\exp(-\gamma\|x-y\|^2)$	Radial basis function kernel
$\tanh(kx.y-\delta)^P$	Sigmoid kernel
P(C)	Probability of Class C
f	Feature
P(C | f)	Probability of Class C on feature f
K	A number of folds
P(i,j)	Pixel location of coordination i and j
[x y 1]T	Transform function for new coordination
T(r)	Transform function for intensity r
$I \oplus S$	Dilation
$I \ominus S$	Erosion

Chapter 4

w	Licence plate width
h	Licence plate height
$\frac{\sigma}{\mu}$	Coefficient variation
μ	Mean value
σ	Standard deviation
(c_i, c_j)	Taillight candidate pairing of candidate c_i and c_j
$\left(1-\frac{\lvert H_i-H_j\rvert}{H_i+H_j}\right)$	Y-axis distance symmetry score of the distance (representing by H) of candidate c_i and c_j
$\left(1-\frac{\lvert A_i-A_j\rvert}{A_i+A_j}\right)$	Area symmetry score of the area of candidate c_i and c_j

$\left(1-\frac{\lvert ARS_i - ARS_j\rvert}{ARS_i + ARS_j}\right)$	Aspect ratio symmetry score of the aspect ratio of candidate c_i and c_j
H1, H2, H3	Height of left, right and licence plate respectively
W1, W2, W3	Width of left, right and licence plate respectively
C1, C2, C3	Center point of left, right and licence plate respectively
Dist. (C_i,C_j)	Distance of coordination C_i and C_j
Avg. (W_i,W_j)	Average of the width of W_i and W_j
Err ($\text{class}_{train} \neq \text{class}_{test}$)	Error rate of test data
$K\left(\mathrm{X}^{\mathrm{i}}, X_{test}\right)$	Test data is verified by kernel function
P(C | t)	Probability of Class C on node t

CHAPTER 1

INTRODUCTION

This chapter presents the introduction to and motivations of this project. Several topics are also indicated: aim and objectives, scope, research methodology, contributions of the research and structure of the report.

1.1 Introduction

According to Interpol's analytical overview report on vehicle crime in a global perspective (Interpol, 2014), there were about 7.2 million records are reported of stolen vehicles worldwide at the end of 2013. Interpol indicates that vehicles are not only stolen for their intrinsic benefits, but are also traded to support other crimes. They can also be used as bomb carriers or in the perpetration of other crimes. There are some indications of economic damage from vehicle crime in 2011. Furthermore, the United Kingdom reported economic damage to vehicle crime totalling about €355 million. In addition, reports from insurance companies in Germany and Australia presented that about €260 million and €422 million, respectively, were lost in vehicle theft.

Car manufacturers have made efforts to increase car security with devices such as infrared locking, vehicle tracking, keyless access, biometric fingerprint car security and immobilisers. Many systems have been proposed in order to protect and assist police to reduce the numbers of vehicle crime. The most popular system which has already been commonly used by the police and law enforcement agencies to identify vehicles is the Automatic Number Plate Recognition (ANPR) system (Anagnostopoulos et al., 2008, Wen et al., 2011, Du et al., 2013). ANPR has been introduced in the previous two decades by using Optical Character Recognition (OCR) techniques and other related works, for example, image enhancement, licence plate localization, character segmentation and character recognition to classify alphanumeric characters on licence plates. The system has been used to identify suspected stolen cars and then retrieve other information such as insurance, taxation and owner details. Furthermore, ANPR has been implemented in many applications such as red-light enforcement, speed limit enforcement, toll systems and parking lot systems.

In the literature, existing ANPR algorithms or systems work well under some controlled conditions for example fixed vehicle position and good illumination. Having analysed previous works on ANPR, there have been a few studies on recognising number plates in low lighting conditions at night. Wanli et al. (2010) used colour based method, HSV colour space, to detect and recognise licence plate.

Although, the reported detection and recognition accuracies are very high but the method is greatly sensitive to light intensities and uneven lighting conditions. Another technique, wavelet transform and edge based method, were introduced by Qi-Chang et al. (2010) to deal with licence plate localization in low light environment. They applied wavelet transform to remove noise and enhance edge pixels. Then, an edge detection method was employed to extract edge lines of licence plate. Licence plate localization rate was reported at about 98%. However, this technique work well in low light conditions only. It cannot not effectively cope with extremely dark images or images captured at night. To solve the problem of varying illumination throughout day and night-time, infrared units have been used. Chen et al. (2012) proposed to use Infrared illuminator to detect position of number plate at night. Then, the number plate detection accuracy was reported at about 98%, tested on 64 night-time images. Infrared cameras are also implemented in some car parking systems. Omnypark (2016) company implements infrared camera in car parking system and system is claimed that can recognise licence plate and robust throughout 24 hours. In addition, images captured from the infrared cameras provide clear and shape images with no different in day and night-time. Moreover, Yanli (2010) presented a semiconductor laser night vision system to recognise licence plate. The system is claimed to work well in real word ANPR applications.

However, ANPR systems cannot accurately identify a car which has had its number plate removed, faked, cloned or covered by dirt. Therefore to prevent crimes where the vehicle licence plate could be false and not recognizable, many researchers have been proposed additional information methods to identify vehicles such as car logo recognition and car make (manufacturer) and model recognition (CMMR). Car logo recognition has been presented in the work of Psyllos et al. (2008). But there is a problem for this method when the logo cannot be detected or is removed by the criminal. For this reason, the vehicle identification system is unreliable. Therefore, a CMMR system could be the robust method to significantly improve the accuracy and reliability of car identification. More information can be drawn from a CMMR system in terms of manufacturers, models, shapes and colours, etc. to help specify cars. This leads to more confidence and accurate results, rather than using only a licence plate (Zafar et al., 2007). Moreover, the method will also be very useful in identifying or recognising and tracking a suspected vehicle across different CCTV cameras. For example, if a suspected vehicle's make and model is reported, the method can be used to identify the same type of vehicle in different CCTV cameras to track the vehicle, instead of using a large number of human operators to check all the CCTVs, which is very time consuming.

1.2 Research motivations

CMMR techniques have been studied as a part of intelligent transport systems in the past decade. Variety of car appearances, for example car body shape, headlight shape, taillight shape, logo, and key points (texture) were implemented in literature (Dlagnekov, 2005, Santos and Correia, 2009, Psyllos et al., 2011). Many classifiers and classification techniques were also used in previous CMMR works, such as k-nearest neighbours (k-NN), decision tree (DT), support vector machine (SVM), neural networks, Naïve Bayes and ensemble methods.

As analysed of previous algorithms and studies, most of them were implemented in daytime where lighting conditions are good and without occlusions (Petrovic and Coote, 2004a, Dlagnekov, 2005, Kazemi et al., 2007, Psyllos et al., 2011, Kafai and Bhanu, 2012). In addition, experimental results in these works were reported with high classification accuracy, more than 90%. However, there are a few published works dedicating to analyse vehicle at night but they do not directly solve a problem of CMMR, for example, driver assistance systems (Wang et al., 2005) and vehicle type classification (Gritsch et al., 2009).

There are many challenges to be overcome to make CMMR techniques work at night. This research is aimed to solve the followings:

1) Limited features: due to low lighting conditions, vehicles' appearances are reduced to only a small number of features, e.g. headlights, taillights, licence plate shapes and positions, are available.

2) Classification technique: there are a large number of existing classification methods. What is the most suitable one for such application.

Car's appearances used in daytime techniques are being reduced to headlight, taillight and licence plate because of low lighting levels or uneven lighting at night. In addition, another problem in image capture at night is reflections which can occur from many light-sources, e.g. street lamps, head-lights, tail-lights and brake-lights of other cars. Light reflections can fade or blur car appearances. However, existing techniques are not suitable for night-time conditions. Therefore, CMMR technique at night is then worth of investigation. This research develops technique to recognise car make and model which consists of determining features from available appearances of car images at night and developing classification technique. In addition, CMMR strategy to be used in real world is also investigated and presented.

To date, CMMR in limited lighting still remains challenging and requires more research to determine good solutions. At night, image recognition is a difficult task due to the image's appearances being faded. However, there are a few published works dedicating to recognizing CMM at night. In the past, various approaches have been presented to solve vehicle recognition at night, but they do not directly solve CMMR problems, for example, driver assistance systems (Wang et al., 2005) and vehicle type classification (Gritsch et al., 2009). This research, therefore, will present the CMMR method at night.

The technique is based on a state-of-the-art of pattern recognition system applied to recognise car make and model in an image. The system begins with image pre-processing which manipulates image characteristics to make them suitable for the next process. Then, car feature extraction is performed in order to obtain features to classify car models. Last, the classification process uses the obtained features to train the classifier and the classifier then can predict an unknown car's model with car-trained models.

In the feature extraction process, the presented method is challenged by the limited features at night. Available data in a car's image at night are headlight, taillight and licence plate. Other appearances might be seen, for example, logo, grill, colour and car shape. However, there is another problem in image capture at night, reflections. Reflections can occur from many light-sources, such as street lamps, head-lights, tail-lights and brake-lights of other cars. Light reflections can fade or blur car appearances. Therefore, the method is carefully considered to choose available data and distinguishable features in order to gain high prediction performance.

In real world images, design features might be missed by the detection that would lead to decreased performance of the proposed method. The presented method, thus, deals with this situation. To solve this problem, the technique finds and uses the possible or available features to classify car make and model and the classification accuracy is satisfied.

Last, the classification method is presented to classify features obtained. The classification accuracy should be as high as possible. The difficult of this stage is how to find the optimum parameters which are to be appropriated to the selected classifier. In addition, classification strategy is concerned with respect to the most suitable approach to the problem.

1.3 Aim and objectives

This research aims to develop a new CMMR method in low-lighting conditions at night by using new pattern recognition and computer vision techniques. The presented technique not only classifies car make and model but also should increase recognition accuracy compared to existing methods. In addition, this research is dedicated to work at night, so the work should robustly handle missing data used in real-world applications.

The objectives of this research are:

1) To investigate and present distinguished car features to classify car make and model.
2) To develop a technique for handling missing features. The method will make this research robust in real-world implementations.
3) To develop a classification technique. The technique will present classification strategy and classifiers used in order to have high classification accuracy.
4) To develop a new CMMR method which uses real-world data.

The proposed method could be used in many systems: parking lots, tolls, traffic surveillance and intelligence transport. Especially, the study focuses on the law enforcement systems which are used to assist the authorities to automatically identify vehicles of interest from images or videos acquired from cameras. Furthermore, this method can support additional information to traditional ANPR systems when the licence plate is unable to identify the vehicle from many reasons, such as dirty, fake and distorted licence plates.

1.4 Scope of the research

CMMR work is classified into two main light conditions: day and night-time. A variety of available features can be obtained in daytime, such as edge features, contour features, texture features and other features. Unlike CMMR in daytime, CMMR at night have a difficult task when many features are faded.

At night, light intensity can be roughly divided by two areas: urban (medium dark) and rural (extreme dark). In urban areas, there are many light sources, such as street lamps, head-lights, tail-lights and brake-lights of other cars. Therefore, it is not too dark in these areas and light intensity is more than in rural areas. Furthermore, there are many nuisance lights in urban areas, more so than rural areas. This study focuses on CMMR in the urban area and aims to solve the problem of CMMR at night. The images used are captured in fixed view and distance because the proposed work focuses only how to recognise a car's body. The research finds salient obtainable appearances for CMMR. In addition, suitable classification technique is also studied in order to have high classification accuracy.

1.5 Research methodology

The research methodology starts with the literature review; published papers were selected from related areas: image processing, computer vision, pattern recognition, ANPR and CMMR.

Second, the CMMR framework is defined based on a pattern recognition system consisting of image pre-processing, feature extraction and classification process.

Third, distinguished features are selected from available appearances in order to classify CMM with high classification performance. In addition, the missing feature handling method is presented, which is designed to make the research technique more robust.

Last, the best classification method is presented from a variety of classifiers and classification techniques. In addition, experiments are conducted to evaluate the proposed method. Then the discussion of results is provided with respect to supported advantages and disadvantages of the presented method.

The main contributions of this research are:

1) To the author's knowledge, this study is the first work that presents a method to classify car make and models under limited lighting conditions at night.
2) Distinguished features and missing features handling strategy are presented for CMMR at night.
3) Binary class classification strategy is introduced to recognise car make and model of interest, which can be applied in real-world applications, such as traffic law enforcement and intelligence transport systems.

1.6 Thesis structure

The remainder chapters of this report are structured as follows.

Chapter 2 provides the literature review starting with pattern recognition systems, image processing and computer vision techniques. Algorithms of recognition processes, classifiers, feature selection techniques and classification performance evaluations are presented. In addition, a variety of techniques in image and computer vision, such as image contrast enhancement, edge detection, corner detection, texture extractors and object representation are reviewed.

Chapter 3 reviews previous CMMR techniques. The chapter consists of many sections such as a general CMMR system, image pre-processing techniques, feature extraction, classification process. This chapter also presents taillight detection and licence plate detection techniques which might be used in the research.

Chapter 4 gives the proposed CMMR method focusing on the details of the process and algorithms. The presented method has three main processes: feature extraction process, optimum feature selection and classification process. First, the feature extraction is the process to detect key points and select distinguished features, including several steps, image enhancement, taillight detection and licence plate localization processes. Then, optimum features are selected by applying a feature selection method. Last, the classification method is presented in a classification process to predict car make and model.

Chapter 5 provides experimental results including system implementation details, machine specifications, software tools, dataset creation and the evaluation of results. Various classifiers are also implemented on creation database for comparison with the proposed method.

Chapter 6 summarises what has been achieved in the project. The conclusions and the possible directions for future works are described.

CHAPTER 2

LITERATURE REVIEW

Car make and model recognition in an image applies knowledge from several fields to solve this problem: pattern recognition, image processing and computer vision. This chapter explores knowledge of pattern recognition, which is an important technique in the proposed research. In the proposed classification process, a pattern recognition method is employed to train a machine, and then it can predict an unknown car's model to the most similar class by its pattern. The pattern recognition system and techniques are provided and related topics; classifiers, classifier combination, feature selection and classification performance evaluation are also introduced.

2.1 Pattern recognition techniques

It is easy for humans to recognise the difference between objects such as fruits, characters and human faces. Humans might use colour, texture, and shape to classify kinds of fruit (such as classifying apple from orange). In character recognition, people can correctly classify a letter in a variety of conditions, for example, small, large, handwritten, rotated and machine printed. In addition, parents might recognise their children in a crowd of students and furthermore they could remember the differences between their twin children. However, it is difficult to teach a machine how to do the same. Pattern recognition is the method that humans have employed to get machines to learn and make decisions through the knowledge of a designer for a specific problem. For more than half century, a variety of pattern recognition approaches have been studied and proposed to solve problems in several engineering and science fields, such as machine vision, data mining, biometrics, marketing, medical imaging, speech recognition, remote sensing, artificial intelligence and psychology (Jain et al., 2000).

Pattern is “as an opposite of a chaos; it is an entity, vaguely defined” (Watanabe, 1985). Pattern is a description of an object or something of interest which is similar for the objects in the same class (Dougherty, 2013). In my understanding, patterns are the characteristic properties of an object to which objects in the same class should have similar but not identical patterns. Pattern recognition is the method or process of how a machine can learn from example characteristic parameters to distinguish a test subject into a predefined class. Pattern recognition approaches are divided into four main methods: 1) template matching, 2) statistical pattern recognition, 3) syntactic or structural matching, and 4) neural networks.

1) Template matching

Template matching is the technique to recognise an unknown object by comparing it with predefined templates. The most similar template is assigned to be the class of the test object.

2) Statistical approach

In a statistical pattern recognition method, object patterns are measured as numerical values. Then the classifier learns from example pattern values and defines class boundaries by a statistical method. After assigned class decision edges, the test object can be predicted to an appropriate class.

3) Syntactic approach

Unlike a statistical approach, a syntactic or structural method uses pattern structural information for classification and description. Each pattern is represented in a structural string of a formal language. To classify a test object, the structural similarity of the pattern is measured and the nearest structure is assigned as the class of the test object.

4) Neural networks

Neural networks can be viewed as massively parallel computing systems consisting of an extremely large number of processors with many connections. Neural network models typically consist of nodes simulating a human nerve system connecting with weighted direct edges. With the model, neural networks can learn in the training process, adapt to data and deal with complex nonlinear problems (Jain et al., 2000).

This research aims to recognise car makes and models as object recognition in images by using a feature-based method. In addition, the research requires high prediction accuracy of CMMs. Statistical pattern recognition seems to be appropriate and therefore this research applies a statistical pattern recognition method.

In a statistical technique, each pattern is measured in a set of scalar values which are the characteristic properties of the object. These values can be called features which are plotted as points in a feature space. In the training process, the objective of classification is to establish decision boundaries in the feature space which separate features belonging to difference classes. In the statistical decision theoretic approach, the decision boundaries are determined by the probability distributions of the features belonging to each class (Jain et al., 2000). The statistical pattern recognition system is operated in two modes: training (learning) and classification (testing). A typical statistical pattern recognition system, shown in figure 2.1, contains pre-processing, feature extraction or selection, and classification.

1) Pre-processing is used to manipulate input data in order to adjust, improve and prepare the data before sending it to the next process. Acquired data or patterns can be affected by the surrounding environment, such as a complex background and noise. The pre-processing methods, amplifying patterns of

interest, removing noise, normalizing the pattern and data transformation, are implemented.

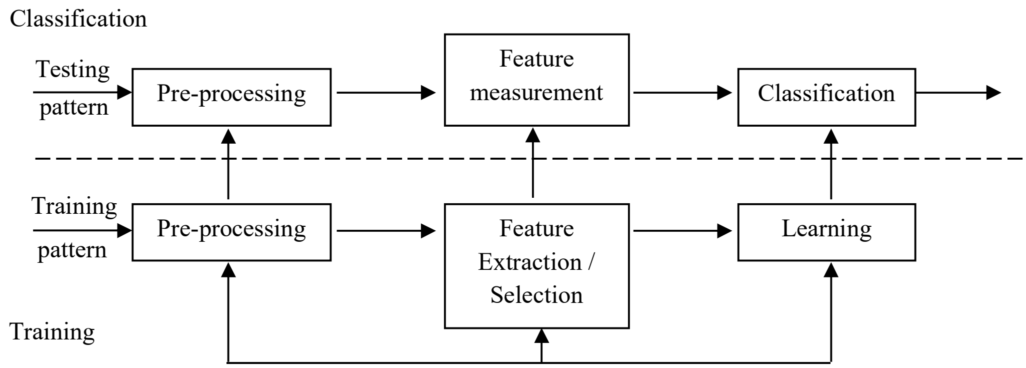


Figure 2.1: Statistical pattern recognition system (Dougherty, 2013).

2) The feature extraction stage aims to obtain sufficient data (patterns, features) that can distinguish an object from other classes. In addition, relevant feature selection may be implemented in order to increase classification accuracy and reduce computation times.

3) Classification is the process to assign an unknown object to a certain class based on the feature information. In the training process, a classifier learns or trains from obtained features and then decision boundaries are determined for each class. In the classification process, the classifier predicts the test object by comparing it to the trained model and then assigns a class to the test object.

2.2 Supervised and unsupervised methods

The recognition technique can be divided into two types: supervised classification and unsupervised classification. A supervised method is a classification technique making decisions from training examples. In a supervised learning training process, a classifier is trained by using pattern values of examples associated with class labels. A classifier learns parameters from a training set and then defines decision boundaries of the classes. Last the in classification process, the unknown object with its features is assigned to the most similar class based on the classifier technique used. Unlike a supervised classification method, an unsupervised classification technique does not require training data and predefined classes. Many applications find it difficult, expensive or impossible to label a training sample with its true category (Dougherty, 2013). Instead, this method classifies an object to an appropriate group based on the similarities among their patterns. In this research, a supervised classification method is used due to the aim of the study to recognise each CMM, not grouping car models.

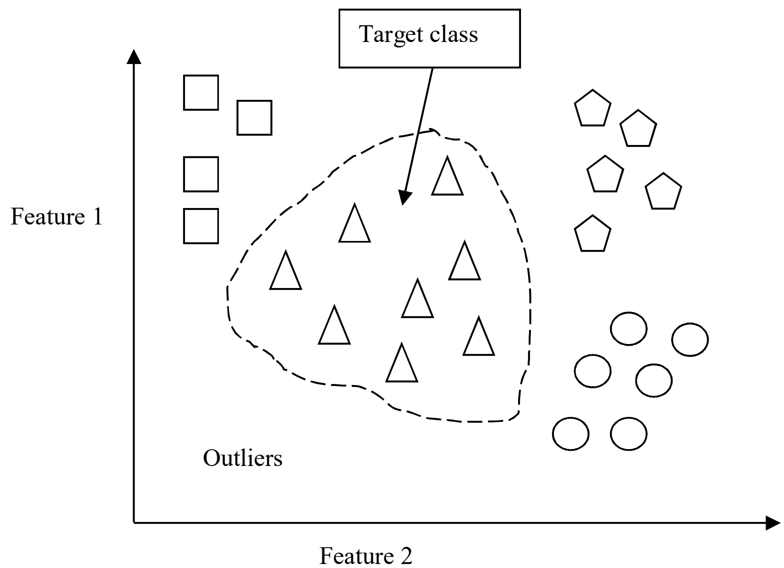


Figure 2.2: One class classification diagram.

2.3 Multi-class and one-class classification

Multi-class classification is the technique to classify a test object to a class of more than two classes, for example character recognition, bioinformatics recognition and object recognition. In this method, the classifier learns with enough available dataset for all classes and then defines decision boundaries of each class. Unlike a multi-class classification problem, a one-class classification problem is a special case of the binary classification method where only data from one class is of interest or available (Khan and Madden, 2014). This class is called the target class, shown in figure 2.2. The other class, which is called the outlier class, can be sampled very sparsely, or can be totally absent. It might be the outlier class is very hard to measure. The technique of one-class classification is to define a decision boundary around the positive (target) class. The boundary minimizes the error of misclassification as much as possible (Khan and Madden, 2014).

2.4 Feature selection

Feature selection is the process to select only potential or relevant features as the feature subset in order to increase the classification rate and reduce the process's computation times. Figure 2.3 shows a feature selection scheme. Basically, this process is done in an off-line operation and the optimum feature subset is used when implemented in real applications. Most feature selection methods use classification error of a feature subset to evaluate its effectiveness (Jain et al., 2000). A feature subset with the smallest prediction error is selected for use in the system. In the study by Chadrashekar et al. (2014), feature selection methods are analysed and can be divided into three categories: filter, wrapper and embedded methods.

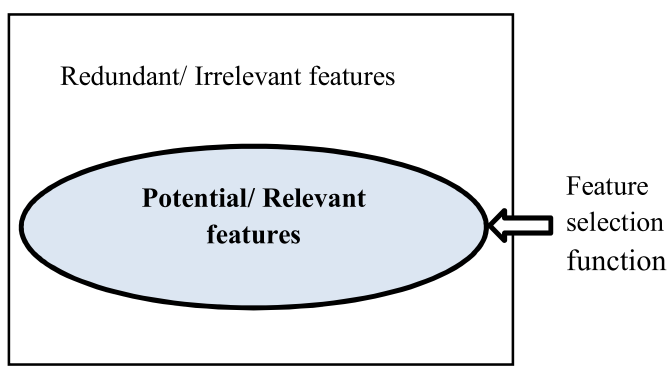


Figure 2.3: Feature selection scheme.

First, a filter technique selects relevant features by ranking score. A ranking function is applied to all features in order to give ranking score values. Then, the scores are used to filter out less relevant (lower scored) features. There are a number of ranking methods, such as Chi square (Liu and Setiono, 1995), Information gain, Relief algorithm (Kira and Rendell, 1992) and Soap algorithm (Ruiz et al., 2003). The advantages of a filter technique are less computation time and avoiding the over-fitting problem. The problems of this method are that a redundant subset might be obtained and the feature subset may not enable global optimization.

Second, unlike a filter method, a wrapper method attempts to find the best feature subset by a search algorithm. There are many different search algorithms, including sequence feature selection, heuristic search algorithm and exhaustive search algorithm, used to find the best feature subset. Firstly, the sequence feature searches – sequential forward selection, sequential backward selection, sequential floating forward selection, sequential floating backward selection – will either grow or shrink features to define several feature subsets. Then, a classification error criteria function is evaluated to search for the optimum feature subset. Secondly, a heuristic algorithm, such as a genetic algorithm (GA) or particle swarm optimisation is the technique to find the optimum feature subset by applied population search. This method defines a termination condition to stop the iteration of operations that can reduce the computation time of evaluating all possible feature subsets. After termination, the result might be a near optimum or the optimum result. Lastly, an exhaustive search method is the technique that guarantees obtaining the optimum subset. However, this method is reported with very large computational times.

Last, an ensemble method combines feature ranking and classifier in order to reduce computation time of the wrapper method. For example, Setiono and Liu (1997) presented a combination of feature weighting and neural network which reported high prediction accuracy and reduced a large number of features. In addition, an ensemble of a ranking method and support vector machine (SVM), called SVM-recursive feature elimination, is used to select optimum features of gene classification (Mundra and Rajapakse, 2010).

2.5 Classifiers

A classifier is an important method in a classification process. In the training process, a classifier technique learns from a dataset (training data) associated with class labels in order to create trained models. In the classification process, the classifier assigns test data against the trained data to a predesigned class. A variety of classifier techniques has been presented in many classification problems, such as Logical based techniques (decision tree, rule based), Perceptron-based techniques (neural networks, radial basis function), statistical based techniques (Naïve Bayes classifier, Bayesian networks), instance based techniques (k-nearest neighbours) and support vector machine (Kotsiantis, 2007).

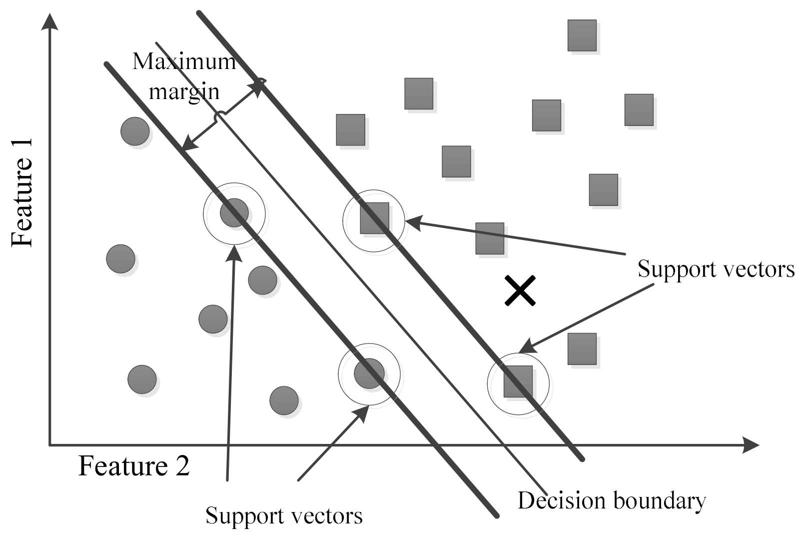


Figure 2.4: Support vector machine.

1) Support vector machine

Support vector machine (SVM) is a classifier based on creating decision boundaries (hyper-plane, linear cutting edge) in vector space in order to classify data into two classes, proposed by Vapnik (1995). Then, the method creates a margin (edge) both sides of the hyper-plane and maximizes the distance between the margins to reduce the upper bound on the expected generalization error (Kotsiantis, 2007). The closet vectors of each class are called support vectors.

Figure 2.4 shows an SVM image and its support vectors. The unclassified data is assigned to a predefined class by measuring with the support vectors. However, in many real-world problems, a linear hyper-plane cannot clearly separate data due to data containing misclassified instances. The solution to this problem is to map data into a high dimensional space by applying a kernel function. Some basic kernel functions are the following:

1) Polynomial: $K(x,y) = (x.y+1)^P$
2) Radial basis function: $K(x,y) = \exp(-\gamma\|x-y\|^2)$, $\gamma=1/2\sigma^2$
3) Sigmoid: $K(x,y) = \tanh(kx.y-\delta)^P$

It has been proven that the classification accuracy of SVM will improve when optimized parameters are used. Therefore, to increase the performance of an SVM classifier, it will need to train the SVM by optimized parameters. The advantage of this method is providing high prediction accuracy. However, the technique's computation time will be very large for tuning optimum parameters.

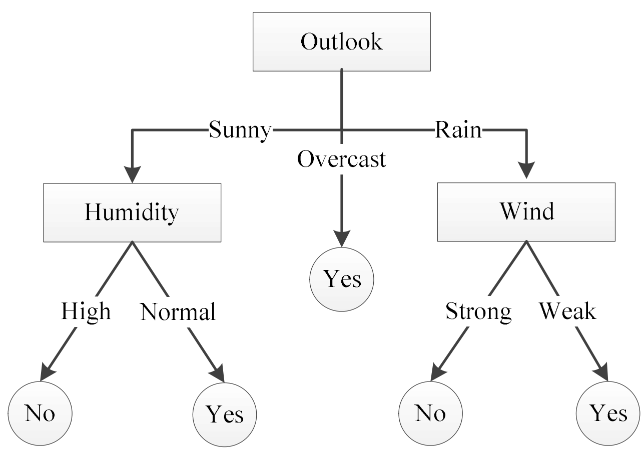


Figure 2.5: Decision tree for the concept 'going out for tennis'.

2) Decision tree

A decision tree (DT) classifier is the logical based technique classifier. A decision tree consists of a root node, internal nodes and leaves. The most discriminant feature is considered as the root node. Each internal node represents an attribute or feature of the training set and leaves are shown as a class label. Many techniques have been used to measure the best feature, such as entropy, information gain, Gini impurity and ReliefF algorithm. Decision tree learning is a method to learn from a training set and choose the best parameter or value to separate classes in every node (features). There are many learning methods, for example, ID3, C4.5, CART and CHAID. Figure 2.5 is an example of a decision tree. A decision tree structure might be complex or not generalize from training data, known as over-fitting. Pruning is a technique used to avoid over-fitting. Decision tree over-fitting may lead to prediction error. The advantages of decision trees are that they are able to handle both numerical and nominal features and have an easy to understand structure. The problems of decision trees are that they are unsuitable to predict a continuous feature and expensive and time consuming to build in complex classification.

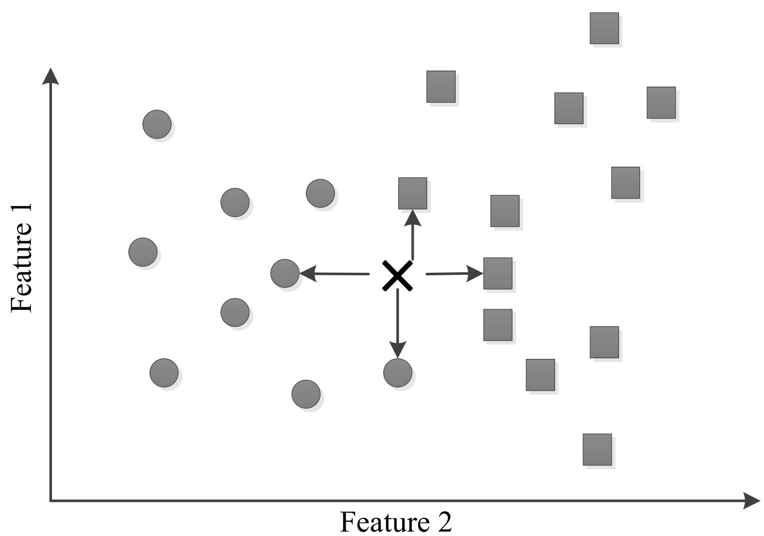


Figure 2.6: K-nearest neighbours.

3) Nearest neighbour

The k-nearest neighbours (kNNs) method is the most simple classification algorithm. The k-NN algorithm is the instance–based technique classifying an unknown object to a class of closest neighbours, shown in figure 2.6. In a one-nearest neighbour (1-NN) classifier, a class where feature vectors are nearest to the test instance is determined. In a system with k more than 1, the classes of the closest k are extracted. Then, the majority vote of those extracted classes is applied to verify the final class (answer). The disadvantage of this method is that it requires high computation time in the classification process and is sensitive to irrelevant features.

4) Naïve Bayes

A naïve Bayes classifier is a statistical learning approach by applying Bayes's rule. The classifier technique first calculates a prior probability of each class from their features, given in equation 2.1 where *C* is a class, *P(C)* is a probability of class *C* and $f_1, f_2, f_3, ..f_n$ are features.

$$P(C|f_1, f_2, f_3, ..f_n) = \frac{P(C) \cdot P(f_1, f_2, f_3, ..f_n|C)}{P(f_1, f_2, f_3, ..f_n)} \qquad (2.1)$$

Then to classify unknown data, a likelihood method is employed and the maximum of a posterior probability class is assigned to be a class of unknown data. Naïve Bayes prediction can be calculated as defined in equation 2.2 where *k* is the number of classes and *n* is the number of likelihood.

$$Prediction = \max_{k \in \{1,..k\}} P(C_k) \prod_{i=1}^{n} P(f_i|C_k) \qquad (2.2)$$

5) Artificial Neural Networks

An artificial neural network (ANN) classifier is inspired by the human brain system. Each node of an ANN simulates a neuron in the brain system. The neurons connect to other neurons with a numerical weight. An ANN learns or trains from the weights of node connections by a learning method. Back propagation is a typical learning algorithm applying to an ANN. The back propagation technique computes input data, weights and error in the designed ANN. Then, back propagation learns and adjusts weights in order to minimize error. Figure 2.7 illustrates an example of a two-layer ANN.

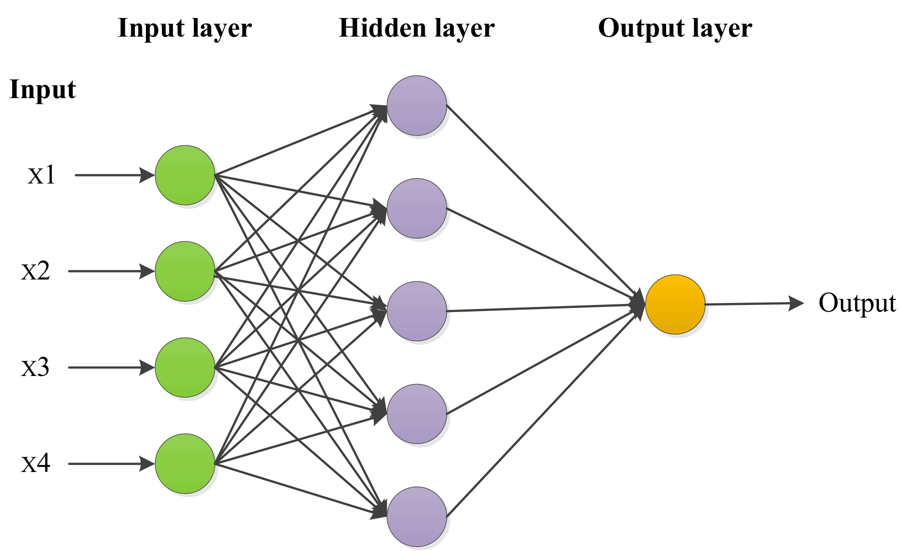


Figure 2.7: A simple two-layer ANN.

2.6 Ensemble of classifiers

A classifier performs the best learning in some local area of a feature space. They may classify the same test data with different results depending on their technique and decision making. An ensemble of classifiers is implemented to deal with several data distributions (high variance) in order to improve classification accuracy. Figure 2.8 displays an overview of a classifier ensemble system. An ensemble technique typically consists of training data and a classifier. The classifier learns from the training set and then defines a decision edge which minimizes prediction error for unknown data. There are a number of ensemble learning methods, such as Bagging, Boosting, Adaboost, Stack generalization and Mixture of experts. In the Bagging technique, a classifier learns from a random training subset, generating several trained models for each random dataset. After that, all models are aggregated by a voting method with equal weight to decide the final prediction. The aim of this method is to reduce the variance of data by randomly using a training subset with a number of ensembles. A Boosting method is an iterative learning technique in order to improve classification performance in repetitive processes. The technique learns from misclassified data in the previous step. It has been proven that the boosting technique improves the classification performance and outperforms Bagging performance, but it may lead to over-fitting. In addition, an improved version of the boosting technique is Adaboost (adaptive boosting). In a stack generalization ensemble, the technique uses two level of a hierarchy scheme to reduce variance of data.

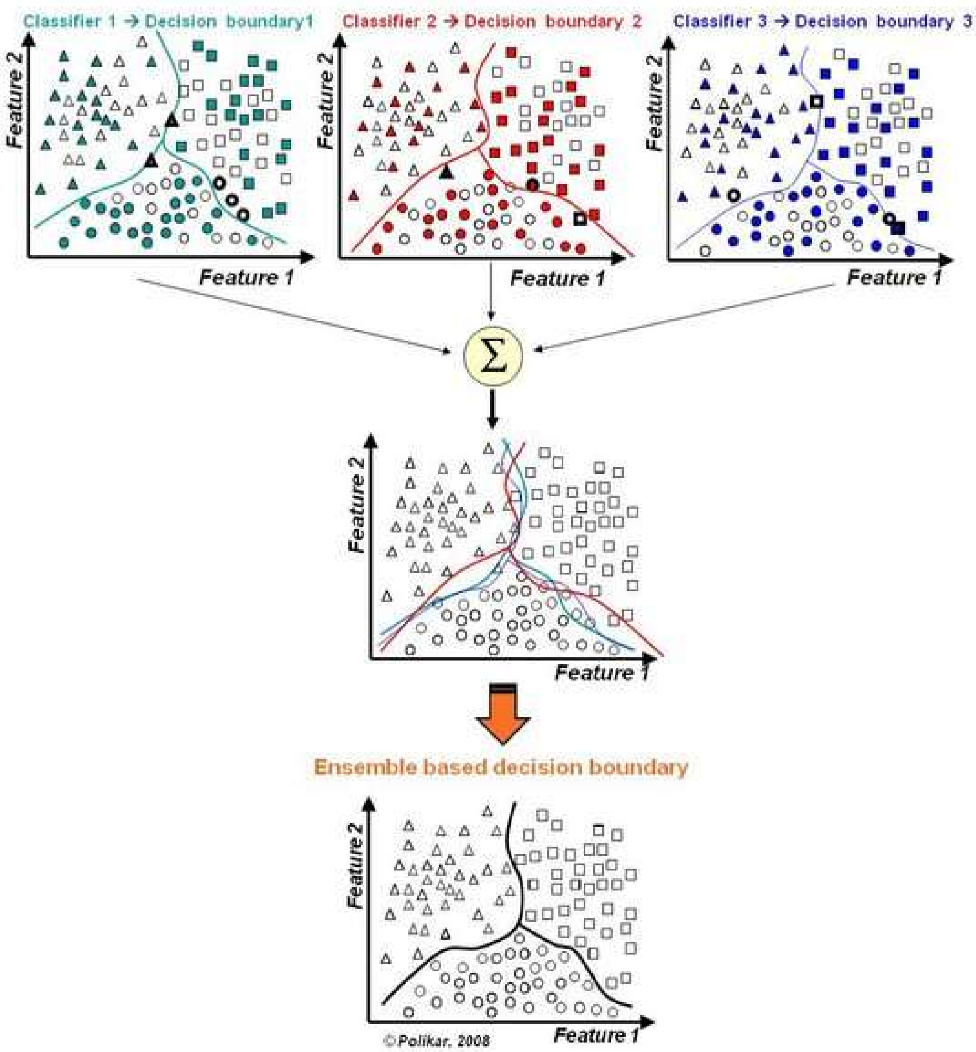


Figure 2.8: Combining an ensemble of classifiers (Polikar, 2006).

In the first level, several classifiers train with the dataset and then they are combined with a combiner to make the final prediction. Cross-validation is a typical method used to evaluate the prediction performance. Misclassified data from the first level is verified again in the second level. Last, the mixture of experts is the combination of variety of classifiers to make prediction together. An ensemble combination is the method to combine results of each ensemble to make the final prediction. There are a number of combination techniques, such as voting, weighted voting, Borda count, averaging, minimum and maximum.

2.7 Class imbalance problem

Class imbalance is a common problem in many real-world classification works. The problem arises when one class's examples, positive class or minority class, are less than another class, known as the negative or majority class. Class imbalance makes it difficult for to classifiers to learn on the given dataset (Japkowicz and Stephen, 2002). For example, having a dataset with ratio 1:100, a classifier will maximize classification accuracy. Then, the accuracy will be obtained 99% except by the minority 1% class. Several techniques have been presented to solve the problem of class imbalance including data sampling, algorithm approaches and cost sensitivity (Galar et al., 2012). First, the data sampling method aims to balance the class distribution at the data level by applying either random under-sampling of the majority class or over-sampling examples of the minority class method. Second, algorithm approaches modify the existing classifier and techniques to classify the imbalanced dataset. Last, cost-sensitive methods try different misclassification cost to minimize error of both classes.

2.8 Classification performance evaluation

Classification performance can be measured in two ways, classification accuracy and speed time of training and testing. This section gives detailed classification performance evaluation. Generally, classification error is used to measure classification performance. Cross-validation is a general method for evaluating a classifier, in which the method separates the dataset into two subsets, the training set and the test set, while the available dataset or instances are limited. A classifier is learnt from the training data and then the classification performance is obtained on the test data results. Cross-validation is divided into three categories, hold out, k-folds and leave one out methods.

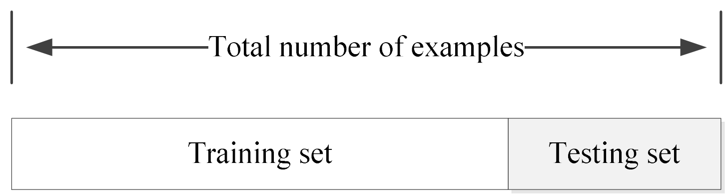


Figure 2.9: Hold out method.

1) Hold out method

Hold out is the simplest method of cross-validation, which divides the dataset into training and testing data, shown in figure 2.9. The proportion of training data can be either one-half or one-third. A classifier learns parameters from the training set. The classification error is measured with the test set. The disadvantage of this method is that both training and testing data are not independent; thus that its evaluation will have a high bias.

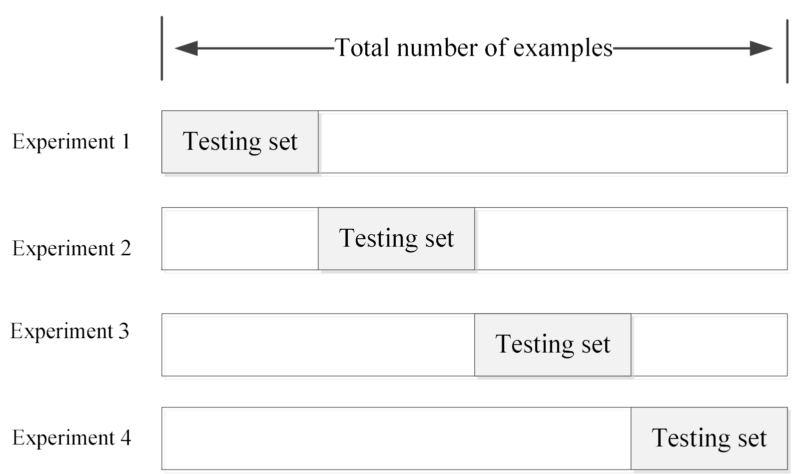


Figure 2.10: K-fold cross validation method, with k=4.

2) K-fold cross validation

In this method, the dataset is separated into k equal-sized subsets and then the experiment is performed k times, shown in figure 2.10. The k-1 subsamples are provided for training data and the rest is used for testing. The error rate can be obtained by averaging over all experiments. The method can reduce the bias of the hold out method and the variance of the resulting estimate is reduced as the subset is increased. The disadvantage of this method is that it is time consuming, depending on the value of k. A common choice for k-fold cross validation is k = 10.

3) Leave one out

Leave one out is a special case of k-fold cross-validation where k is equal to the size of samples. This method uses one sample to test in each experiment and trains with the remaining data. This approach is popular for a problem with small dataset. The problem with this method is that computational time will be very large. Figure 2.11 shows an example of the leave one out method.

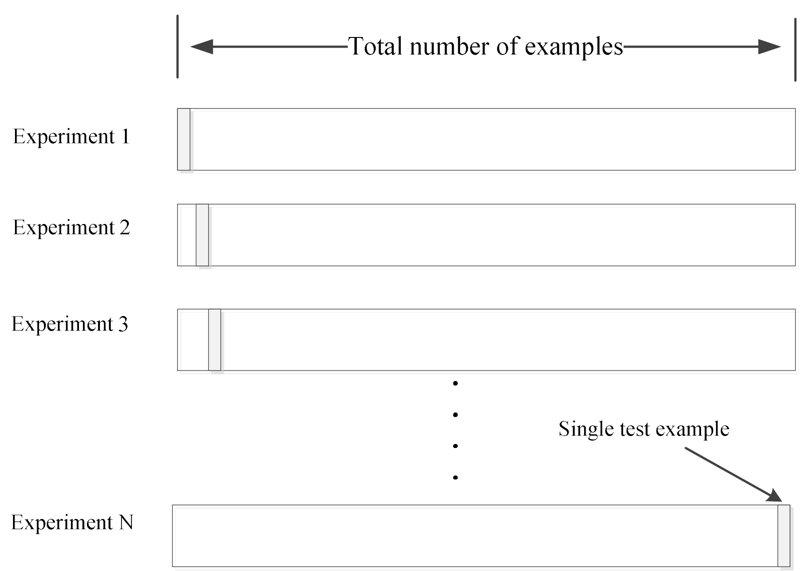


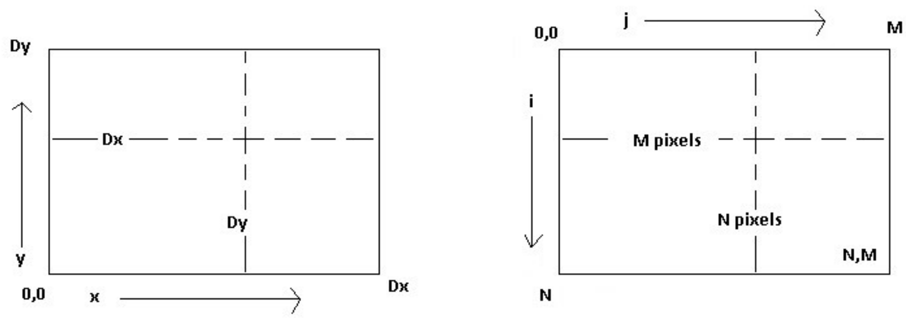
Figure 2.11: Leave one out cross validation.

There are other measures that can be used to evaluate the performance of a classification system, for example, confusion matrix, precision and recall, and receiver operating characteristic (Bradley, 1997).

Computer vision is another field related to this study. The research applies many computer vision methods, such as image processing techniques, region of interest detection, and region representation and description in order to extract features of interest for the recognition process.

2.9 Image processing

This section provides basic knowledge of images such as image element, image representation, colour image model and image histogram.



(a) (b)

Figure 2.12: Image representation. (a) Image element. (b) Matrix representing image.

2.9.1 Image representation

An image can be represented by an N × M matrix. Each element of the matrix can be called pixel p(i,j) which is mapped to an element of image (x,y). The pixels contain a numerical value, for example, 0 or 1 in a binary image. However, the origin in an image and the associated matrix are different. The origin coordinate of an image is located at the lower left corner, whereas the origin point of the matrix is located at the top left corner of matrix. Figure 2.12 shows the relationship between image element and pixel matrix.

As stated earlier, an image element can be identified by pixel coordinates. Figure 2.13 shows pixel indexing associated with an image element.

(0,0) j $\rightarrow$ M

i $\downarrow$ N

p(0,0)	p(0,1)	p(0,2)	p(0,3)	..	p(0,m)
p(1,0)	p(1,1)	p(1,2)	p(1,3)		
p(2,0)	p(2,1)	p(2,2)	p(2,3)		
p(3,0)	p(3,1)	p(3,2)	p(3,3)		
..					
p(n,0)					p(n,m)

Figure 2.13: Example of pixel indexing.

Each pixel at location p(i,j) has a numerical value corresponding to a brightness or intensity value. The intensity value is an integer in the interval [0, L-1] where L is 2^m. The common values of m are 1 and 8, where 1 provides a binary image and 8 provides 256 grey levels. Figures 2.14 and 2.15 illustrate binary and grey scale images, respectively, and some region values.

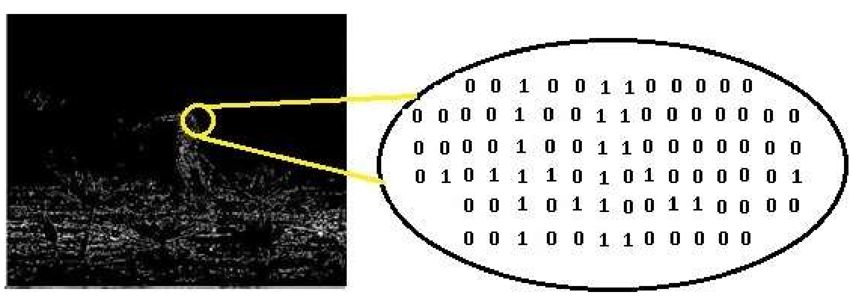


Figure 2.14: Binary image and intensity values.

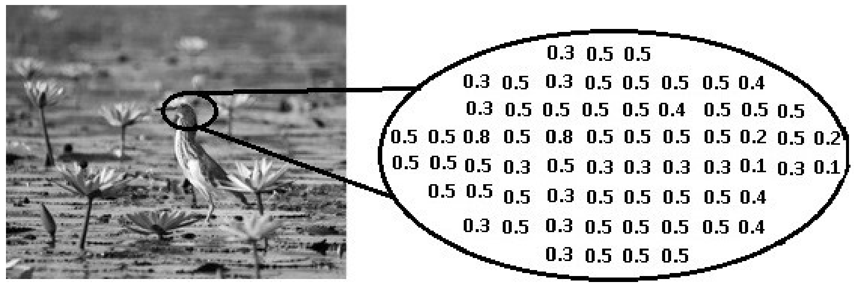


Figure 2.15: Grey scale image and intensity values.

2.9.2 Histogram

A histogram is simple, useful information about an image characteristic. The histogram technique counts the number of pixels at particular grey levels. Figure 2.16(b) shows a histogram graph of the image in 2.16(a). This attribute can be used in many applications such as contrast improvement, object and background segmentation.

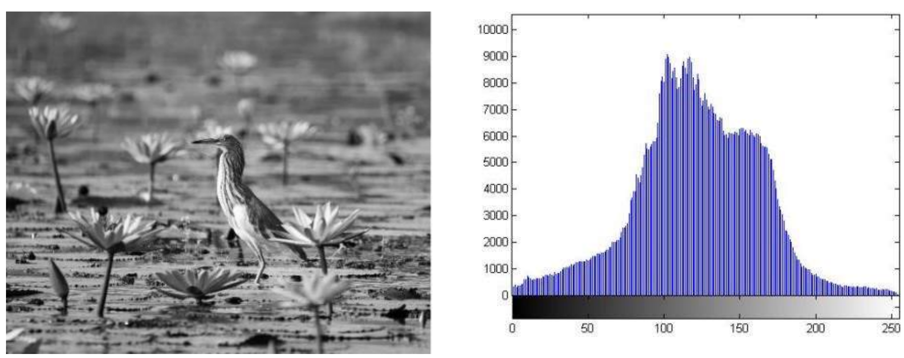
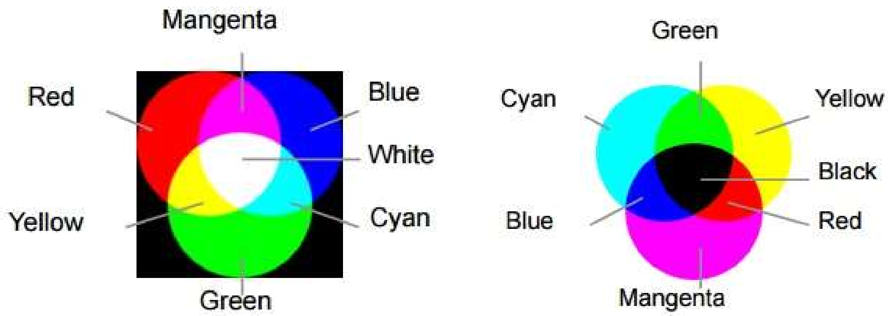


Figure 2.16: Histogram. (a) Grey scale image. (b) Histogram.

2.9.3 Colour image

A colour image is often represented by three or four colour values associated with a pixel. In three-colour channel system, a colour in each pixel is combined by three component colours. There are many three-colour systems used in computer vision systems, such as RGB, YCbCr, L*a*b* and HSV. A four-colour system, for example, CMYK, presents a colour image by combining four colours; cyan, magenta, yellow and black, which is commonly used in the printing industry. Figure 2.17 illustrates RGB and CMYK colour models.



(a) (b)

Figure 2.17: Colour models. (a) RGB model. (b) CMYK model.

RGB colour space is the most commonly used in many applications. The system represents a colour with three components: red, green and blue. If each component uses 8 bits which have integer values from 0 to 255, this makes a total of 16,777,216 possible colours. Figure 2.18 shows an example of an RBG image and each colour value. However, a grey scale image is usually the preferred format for image processing. In cases requiring a grey image, an RGB colour image can be converted to a grey image.

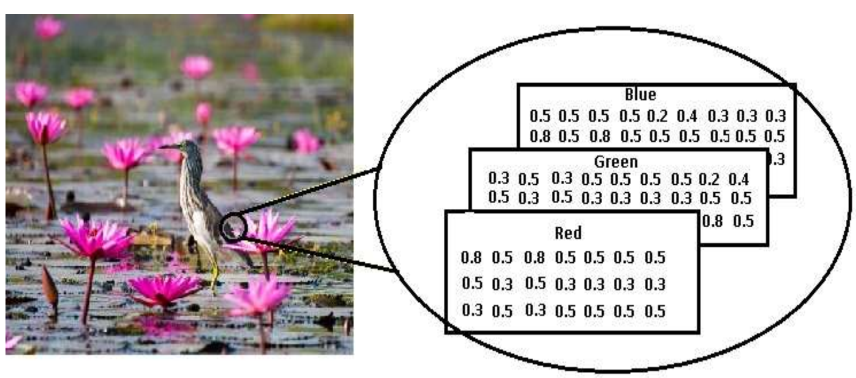


Figure 2.18: RGB colour image and intensity values.

2.9.4 Image geometric transformation

A video camera can be set up in various unfixed views, for example, on left or right sides of roads and on buildings to capture images. Furthermore, several camera distances can be installed and the camera can be zoomed in or out to obtain images. Geometric transforms might be used in real-world applications, which depend on environmental conditions to adjust image properties suitable for predefined parameters.

A geometric transform basically consists of two steps: point transformation and interpolation process. Point transformation is the process to map coordinates of an input image to an output image. Interpolation aims to estimate within original points to a new location. Interpolation methods can be divided into three categories: nearest neighbourhood, linear and bi-cubic interpolation. The most typically used coordinate transformation is the affine transform (Wolberg, 1998), which has the general form as:

$$[x' \; y' \; 1] = [x \; y \; 1]\mathbf{T} = [x \; y \; 1]\begin{bmatrix} t_{11} & t_{12} & 0 \\ t_{21} & t_{22} & 0 \\ t_{31} & t_{32} & 1 \end{bmatrix} \tag{2.3}$$

The affine transforms, rotate, resize, translate and shear, can be expressed as the following five equations:

- Rotation by angle Θ

$$x' = x\,co \quad \Theta + y\,sin\,\Theta$$
$$y' = -x \sin\Theta + y\cos\Theta \tag{2.4}$$

- Resizing

$$x' = ax$$
$$y' = by \tag{2.5}$$

- Translation

$$x' = x + t_x$$
$$y' = y + t_y \tag{2.6}$$

- Shear (vertical)

$$x' = x + s_v y$$
$$y' = y \tag{2.7}$$

- Shear (horizontal)

$$x' = x$$
$$y' = s_h x + y \tag{2.8}$$

As mentioned earlier, images can be taken in several views and distances. Then, some transformations are used in the research.

2.9.5 Contrast enhancement

The objective of this research is implementation in low-light conditions at night, where textures, edges or other appearances of captured images cannot be clearly achieved. Image contrast improvement is an important process in this research to enhance contrast in an image. There are two main techniques to improve contrast in an image: 1) intensity transform, and 2) histogram processing. An intensity transform is the simplest method to modify image contrast, such as image negatives, log transformations, or gamma transformations. The intensity transform technique takes a pixel value of an image and transforms it to a new intensity value by applying a transform function of the form $s = T(r)$, where T is a transformation that converts pixel value r into s intensity. In histogram processing, the method manipulates histogram values in an image in order to improve visual appearances of the image. The traditional histogram processing for contrast enhancement is histogram equalization (HE) which increasingly contrasts on whole image (global enhancement) appearances, shown in figure 2.19. The HE technique begins by calculating the histogram of an image and then computes the probability distribution on each histogram level. Next, all histogram levels are computed a cumulative distribution value. Lastly, pixel values in the original image are mapped to the new value by applying a predefined cumulative distribution function. In addition, HE is applied on separated regions of an image in order to improve local region contrast, called adaptive histogram equalization (Zuiderveld, 1994).

Figure 2.19: Histogram equalization. (a) Original image. (b) Equalized image.

Furthermore, there are many modified histogram equalization techniques which not only enhances contrast of an image but also preserves brightness in some areas of the original image. The brightness preserving method was first presented by Kim (1997), called Bi-Histogram Equalization (BHE). The BHE technique separates histogram levels into two groups by a mean value. Then, HE is applied separately on the groups. Similar to BHE, Dual Sub-Image Histogram Equalization (DSIHE) uses median value to divide histogram levels into two sub-histograms (Wan et al., 1999). The recursive methods, Recursive Mean Separate Histogram Equalization (Chen and Ramli, 2003) and Recursive Sub-image Histogram Equalization (Sim et al., 2007), have been proposed to generalize BHE and DSIHE, respectively. The method generalizes the image histogram by recursively implementing HE on all sub-histograms (more than two). Last, the Recursively Separated Weighting Histogram Equalization (Kim and Chung, 2008) has been presented by applying a weighting function on each sub-histogram separately. The technique consists of three modules: histogram segmentation, histogram weighting and histogram equalization. The method has been claimed to preserve brightness and improve contrast of images better than previous techniques.

2.9.6 Morphological operations

Morphological operations are the methods to alter region boundaries, used for many purposes for instant object structure enhancement (thickening, thinning), region of interest extraction and noise suppression. In this study, many morphological operations are used to process subject images in order to extract regions of interest such as licence plate and taillight positions. In addition, the methods can be used to remove unwanted regions (noise and reflections) which occur in images captured at night. The primary morphological operations are dilation and erosion, which are commonly applied to binary images.

Basically, morphological operations take two pieces of data as input. First is the image which is to be operated on. The second is a structuring element. Then the structuring element is applied (addition or subtraction) to the first image, called a morphological operation.

Dilation is the method to expand the boundaries of regions (white pixels) by an addition operation of image and structure element. Equation 2.7 shows dilation of image I with structure element S. Figure 2.20 shows an example of A images dilated by the structuring element B.

$$D = I \oplus S \tag{2.9}$$

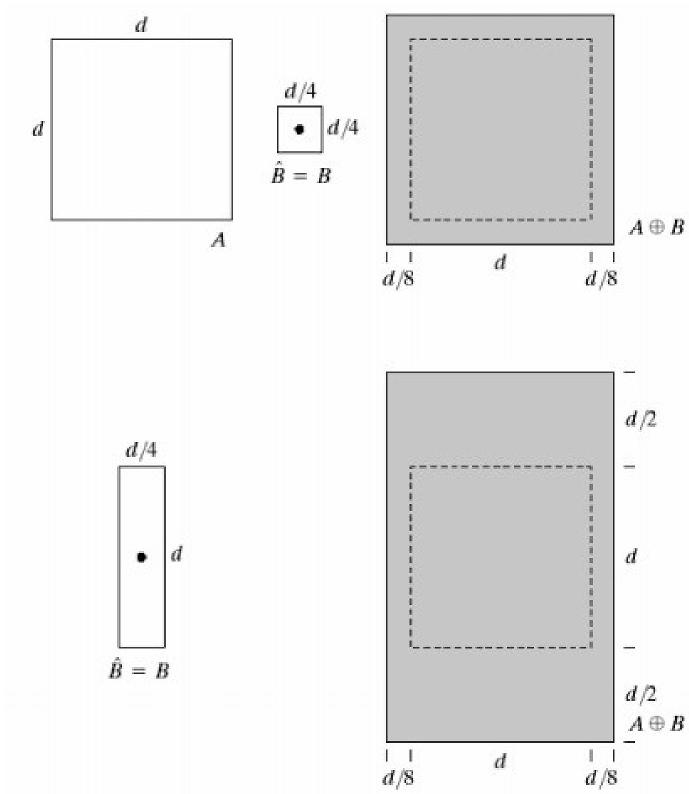


Figure 2.20: Image dilation (Gonzalez and Woods, 2007).

Unlike the dilation method, erosion is the method to gradually reduce the shape of regions. The erosion operator takes two pieces of data as inputs. The first is the image which is to be eroded. The second is a set of coordinate points known as a structuring element. It is this structuring element that determines the precise effect of the erosion on the input image. Figure 2.21 shows an example of A images eroded by the structuring element B. The erosion of an image I by structuring element S is defined as:

$$E = I \ominus S \tag{2.10}$$

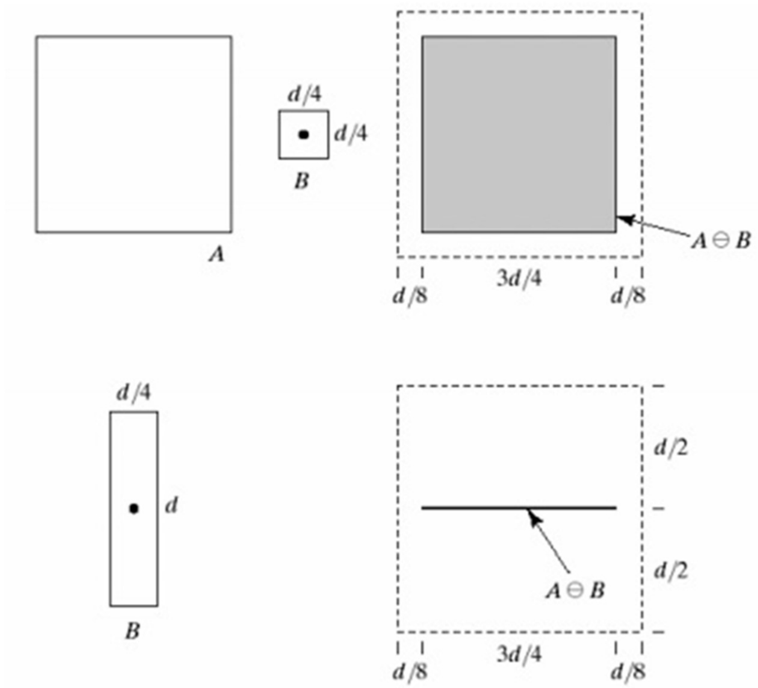


Figure 2.21: Image erosion (Gonzalez and Woods, 2007).

Furthermore, more complex operations are opening and closing operations. A opening technique is the dilation of the erosion image. In contrast, a closing operation is the erosion of the dilation image.

2.10 Feature detection

In this section, feature detection techniques are explored, including edge detection methods and corner detection techniques.

2.10.1 Edge detection

Edges are the primary data of an image which can be utilized in image processing, computer vision and image understanding fields. Important features can be gained from edges such as corners, curves and object shape. In addition, objects or regions of interest and feature extraction can be obtained after edge detection.

This research uses edge information in order to detect objects of interest, such as car, licence plate and taillight positions and feature extraction.

Edges are the significant local changes in image intensity and commonly occur on the boundary of two different regions (Gonzalez and Woods, 2007). There are four fundamental steps of edge detection: 1) edge smoothing, 2) enhancement, 3) detection, and 4) localization. There are many edge detectors and most of them are based on first and second derivatives of the image to find sharp changes of local intensity. There are Roberts, Prewitt, Sobel and Canny edge detectors which is the most popular edge detector. Figure 2.22 shows an example of Sobel vertical edge detection applied to a car image.

(a) (b)

Figure 2.22: Edge detection. (a) Original image. (b) Edge extraction image

2.10.2 Corner detection

Similar to edge information, corners are other appearances used in computer vision that might be implemented in many applications, such as object recognition, image recognition, object tracking and 3D object reconstruction. A corner can be defined as the intersection of two edges or the significant change in terms of intensity in local neighbours. A variety of corner detectors have been presented in previous decades. The first work was proposed by Moravec (1977). The sum of squared differences (SSD) technique is used to measure the local intensity change of each pixel. Then, real corner points are verified by comparing with a predefined threshold. Similar to Moravec's work, Harris and Stephen

(1988) proposed a SSD operation on any directions of a pixel, called a Harris corner detector. A Harris corner detector technique is based on the first derivative to measure the local autocorrelation. The method has reported high performance to detect “L” corners and is invariant to image translation and rotation. Another corner detector, Small Univalve Segment Assimilating Nucleus (SUSAN), was presented by Smith and Brady (1995). The SUSAN technique defines a circle mask (nucleus) and then places an image’s pixels in order to verify a corner pixel. At a corner, the SUSAN area is less than half of a circle mask. SUSAN can be used to both detect edges and corners and was reported insensitive to noise.

2.10.3 Feature description

Feature description is the method to represent and describe feature characteristics in an image. A region or object is represented by a variety of techniques, such as shape and contour (boundary) description. In addition, texture descriptor techniques, SIFT, SURF and HOG, are also reviewed.

Shape representation and description are the processes to describe characteristics of an object or region shape. The descriptions are measured to features and then can be used in object recognition systems and image retrieval applications. Several shape representation and description methods have been presented in the past decade. Zhang and Lu (2004) provided a review of shape representation and description techniques. The techniques can be divided into two main types: contour-based and region-based, shown in figure 2.23. First, the contour-based method aims to represent an object or region of interest by describing its object boundaries. There are many object contour representation methods, such as chain code, polygon, perimeter, wavelet description and contourlet description. Second, a region-based method is the common description of a region such as area, eccentricity, rectangularity and compactness. In the present study, some methods, region area, region aspect ratio and grid description, are used to measure license plate and taillight size, shape and distance in order to obtain features of car make and models.

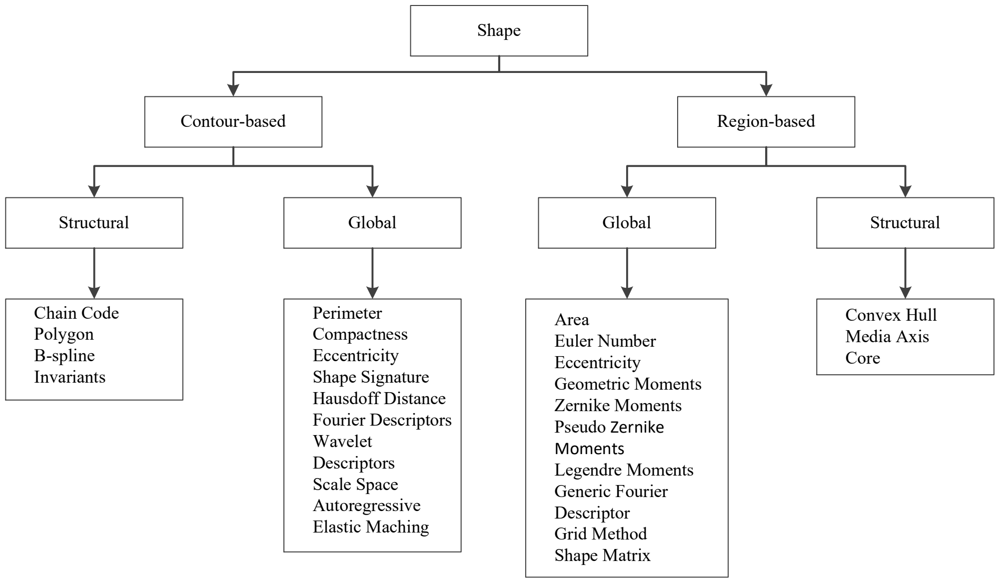


Figure 2.23: Classification of shape representation and description techniques (Zhang and Lu, 2004).

A region area is a basic property of a region which is obtained by counting the number of pixels in a region. However, the property is sensitive to the distance of the image capture.

Region aspect ratio is a proportion of region width and height. This value is used to solve the problem of various image-capture distances. Furthermore, aspect ratio can be used to normalize other features.

Grid description is a method to present the region shape, first proposed by Lu and Sajjanhar (1997) in the area of content-based image retrieval. Basically, in a grid technique, a given shape is overlaid by a grid which consists of fixed size square cells. The grid space should completely cover the shape, as shown in figure 3.13. The grid is then scanned from left to right and top to bottom. The grid cells are assigned the value 1 where the cells are covered by shape and assigned the value 0 for the other cells. For example, the shape in figure 2.24 is represented by the binary sequence 11100000 11111000 01111110 01111111.

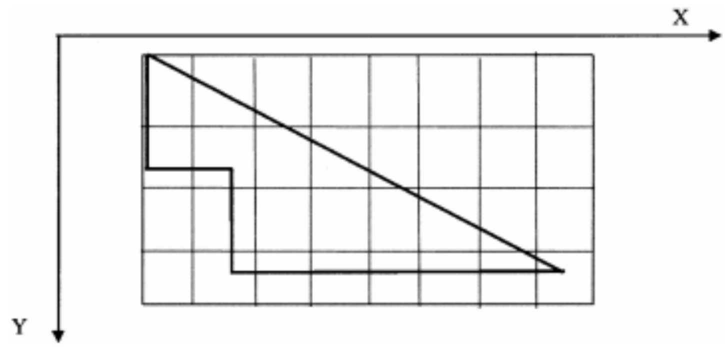


Figure 2.24: Grid method description for region shape (Lu et al., 1997).

2.10.4 Texture description

Texture information is a popular image appearance that is used in image retrieval, understanding, recognition and classification. Image or object patterns may be obtained by applied texture detection. Many texture extraction algorithms are presented by several published works. The reputation method is scale invariant feature transform (SIFT), presented by Lowe (2004). The technique was reported invariant to translation, rotation, scale and other imaging parameters. Another texture descriptor, histogram of gradient (HOG), was proposed by Dalal et al. (2005). The technique was first used to detect pedestrians, and then to detect humans and moving objects, such as animals and vehicles. Some years later, other authors proposed the speed up robust feature (SURF) detector (Bay et al., 2008) which is faster than SIFT and has an acceptable accuracy rate.

CHAPTER 3
CAR MAKE AND MODLE RECOGNITION TECHNIQUES

This chapter gives details of previous CMMR works, techniques and systems. CMMR has been studied over several years with a variety of conditions and parameters. Much research show that it can work well in specific conditions. In addition, the chapter also provides an overview of vehicle recognition systems including the traditional system (automatic number plate recognition) and vehicle class recognition. Furthermore, licence plate and taillight detection techniques, which are the important sub-process of this research, are also reviewed.

3.1 Vehicle recognition

Vehicle recognition (VR) is used as an important process for many intelligent transport systems (ITS), such as traffic law enforcement systems, traffic monitoring systems, traffic management systems, access control systems and toll systems. VR systems can be divided to three recognition system types: 1) automatic number plate recognition, 2) vehicle class recognition, and 3) car make and model recognition. First, a VR process is implemented in a car identification system by using optical character recognition (OCR) to recognise the characters within the licence plate, which can be called automatic number plate recognition (ANPR) or licence plate recognition (LPR).

A recent review of ANPR works and techniques can be seen in the work of Du et al. (2013). The applications of ANPR are widely deployed in a number of systems: parking lot systems, access control systems and law enforcement systems. Figure 3.1 shows an application of an ANPR method for a parking lot system.

Figure 3.1: LPR application in parking lot system (Moviva, 2013).

Second, vehicle class recognition (VCR) is a method used to classify vehicle types, such as van, car, bus, motorcycle and truck, by applying computer vision techniques, such as feature-based, model-based and measurement-based (Chen et al., 2009). Vehicle classification systems are essential for effective transport systems, for example, traffic management and toll systems, and parking lot systems. Figure 3.2 shows a VCR application.

Figure 3.2: VCR application (Procomwave, 2013).

Final, a CMMR system is an essential addition method to significantly improve the accuracy and reliability of car identification systems. More information can be drawn from a CMMR system in terms of manufacturers, models, colours, brand logos, etc. to help specify a car. This leads to more confidence and accurate results, rather than using only on a LPR identification. CMMR is useful in many applications of intelligent transport systems, such as traffic surveillance systems, traffic monitoring systems and traffic law enforcement systems. Figure 3.3 illustrates a CMMR implementation.

Figure 3.3: CMMR application (Procomwave, 2013).

3.2 CMMR techniques

CMMR techniques have been widely studied for intelligent transport systems during the past decade. Generally, a CMMR system consists of three steps: image pre-processing, feature extraction and classification process, illustrated in figure 3.4.

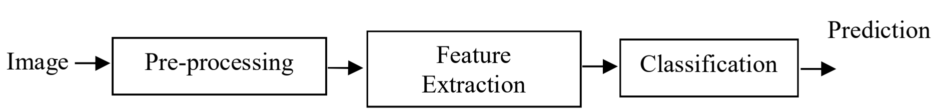


Figure 3.4: General CMMR system.

First, image pre-processing aims to modify, improve or adjust image characteristics before extracting features. Various methods are used in the process, for example, contrast improvement, image resizing, image rotating, image transform, background subtraction, region of interest (ROI) extraction and key point detection. Second, feature extraction is staged to obtain values, parameters or patterns of CMMs which could be used to distinguish car classes. Car features obtained in both front and rear view are car body shape, headlight shape, taillight shape, colour, logo and other appearances. A variety of features has been implemented in CMMR works, for example, geographical feature, edge feature and texture feature. To obtain these features, feature detectors and simple computer vision techniques are applied, such as edge detectors, corner detectors, contour detectors and texture extractors. In addition, some works have presented combined features in order to gain good results, for instance, integrating wavelet and contourlet features (Arzani and Jamzad, 2010) and Pyramid Histogram of Gradient (PHOG) and Gabor features (Zhang, 2013). Lastly, classification is the process to predict a test object with models trained by classifier. This process contains training and testing steps. For the training step, a classifier is trained or learns from obtained features and then defines a decision boundary for those features in order to separate classes. In the testing step, the classifier predicts features of the test object with trained models and then shows a classified result. Many classifiers were used in previous CMMR methods, such as k-NN, decision tree, SVM, neural networks and Naïve Bayes. Furthermore, classification ensemble methods and frameworks are also presented in order to increase classification accuracy and robustness in specific environments.

From the analysed CMMR works, feature-based methods are the majority of CMMR techniques. Several features are presented in order to distinguish CMMs as much as possible. Feature types can be roughly divided into four categories: geographical-based feature, edge-based feature, transform domain-based feature and texture feature.

3.2.1 Geographical-based feature

A geographical feature is a feature which is measured from the object of interest's shape, size, distance and angle to numerical values. This feature has been presented in several CMMR works. Daya et al. (2010) measured geographical features, width, height of ROI in car front view and distance between headlights and a licence plate. Figure 3.5 shows images of ROI and parameter measurement. Nine CMM classes were tested and they reported the prediction accuracy at about 95%.

Figure 3.5: ROI and geographical features measurement (Daya et al., 2010).

The feature was also studied by Santos et al. (2009) to recognise CMM in the rear view. They combined geographical features of car body shape, taillight shape and colour feature. The similarities of each feature were calculated by designed formulas used to classify CMMs. The classification accuracy was reported at 89%, and were experimented on 18 CMMs. Figure 3.6 illustrates an image of car shape extraction and feature measurement.

Figure 3.6: Car shape image and its binary shape extraction (Santos et al., 2009).

In addition, Kafai and Bhanu (2012) proposed this feature type to predict vehicle classes such as sedan, pickup truck, SUV/minivan and unknown. The method started with detecting vehicle position. Then, they localised licence plate position in order to obtain its size and location, which were used to normalise image size and dimension. Next, taillights were segmented out and then features extracted such as taillight size, vehicle mask dimensions, distance and angle between licence plate and taillights. Sequential floating forward selection was used to choose the discriminant features of each vehicle class. In addition, feature selection not only improved classification accuracy but also decreased feature measurement cost. Last, they used dynamic Bayesian networks to predict vehicle classes and the experimental results reported the classification rate better than k-NN, linear discriminant analysis and SVM. Figure 3.7 displays ROI localization.

Figure 3.7: ROI extraction and its measurement (Kafai and Bhanu, 2012).

3.2.2 Edge-based feature

Edge-based feature is a simple characteristic that can be used to recognise objects. A variety of method, such as Sobel edge detector, Canny edge detector, Histogram of Gradients (HOG) and Square mapped gradients (SMG), are utilized to capture car edges, shape and appearances. Petrovic and Cootes (2004) proposed SMG to extract car shape and edge appearances. Experimentally, several features such as raw image, Sobel edge, edge orientation, direct normalised gradients, locally normalised gradients, SMG, Harris corner and spectrum phase have been implemented in order to compare classification performance. They applied

Euclidean distance to find the minimum distance to predict the test object against registered classes. On analysis of many features, the highest CMMR accuracy was 93.3% by using SMG feature. They also presented the matching refinement technique to improve the recognition accuracy. The technique was utilised to translate, rotate and re-scale the ROI area. After refining the image, the classification accuracy improved from 93.3% to 94.4% (Petrovic and Cootes, 2004). In addition, Pearce and Pears (2011) presented a CMMR technique based on Harris corner strength features. The technique first manually marked up three corners of the licence plate in order to obtain its size and position. Then, from the detected licence plate, it can be used to normalise an image by scaling, rotating and skewing. Next, a number of feature extraction methods such as Canny edges, Square mapped gradients (SMG), Harris corners, improved SMG and Locally normalised Harris strengths (LNHS) were applied to obtain features of ROI. Last, two classifiers, k-NN and Naïve Bayes, were implemented to classify make and model of a car in order to compare classification performance. The experimental results showed that Naïve Bayes outperforms k-NN on all features. In addition, both improved SMG and LNHS features with Naïve Bayes were shown to have the best classification accuracy with about 96%. Moreover, Chen et al. (2015) proposed HOG feature and a distance function to classify CMMs. The method first used symmetrical measurement of SURF points to localize vehicle position. Then, the obtained vehicle was divided into 3×6 grid blocks, and each grid block had a HOG detector applied to obtain HOG features. Last, the Hamming distance method was used to classify CMMs; the classification recognition accuracy was reported at 92%. Furthermore, the HOG feature was also used for recognition of CMMs in Lee et al.'s (2013) work. They also presented an algorithm to automatically rotate an image by employing a symmetric technique of key points. This study reported that it can improve the accuracy of a system when testing images are rotated by 0 to 15 degrees.

3.2.3 Transform domain-based feature

A transform domain method is a technique to transform image appearance to high dimensions, which might easily extract salient features in order to increase classification performance. Kazami et al. (2007) presented a curvelet transform to extract CMM shape. They measured different scales of curvelet in order to obtain many feature vectors. The obtained features, they classified CMMs by using three classifiers; SVM (one versus one), k-NN and SVM (one versus all). Classification accuracy was reported at 99%, tested on five CMM classes. With the same algorithm and dataset, Rahati et al. (2008) proposed a contourlet feature replacing the curvelet. The prediction accuracy illustrated equivalence to the previous work. Furthermore, another transform domain method, a Haar-like feature combining Adaboost, was presented for CMMR by Sivaraman and Trivedi (2010). They also introduced an active-learning framework for recognition and tracking of vehicles. The method showed detection rate higher than passive-training vehicle recognition.

3.2.4 Texture based feature

Texture feature is another popular feature used in many recognition works and image retrieval researches. On analyse of CMMR works, the majority of texture extractors are SIFT and SURF. First, SIFT was introduced to classify CMM by Dlagnekov (2005). He experimentally compared the SIFT feature with Eigencar and shape context features. Classification accuracy of SIFT features was better than both features and was reported at about 89%. In addition, SIFT was also proposed to recognise car logos in Psyllos et al.'s (2011) study. The study presented a method to recognise vehicle manufacturer and model by using the combination of vehicle colour, shape and logo. The technique first used a sliding concentric window to detect licence plate position. Then, vehicle mask was extracted by referencing to licence plate position, size and dimensions. The recognition system was divided into three parts: colour, manufacturer and model recognition. Neural networks were applied in the recognition process and reported

85% prediction accuracy for manufacturer and 54% for model recognition. However, the approach depended on logo recognition. If the logo cannot be detected, it will decrease the whole CMMR performance.

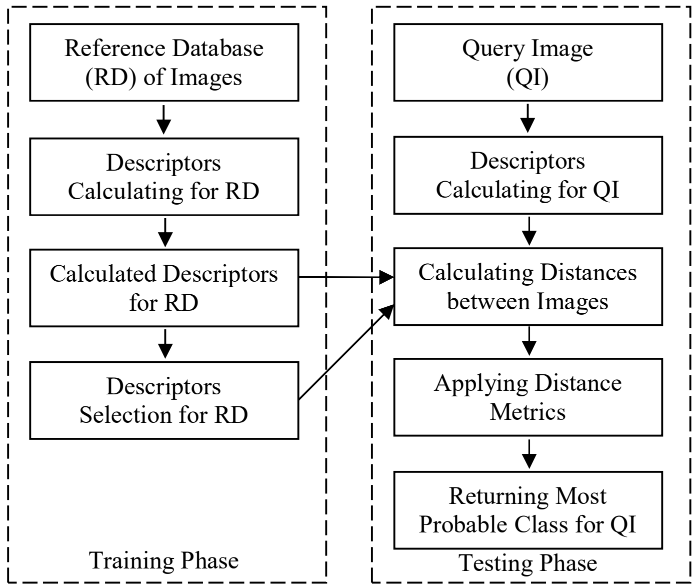


Figure 3.8: Framework of real-time CMMR approach (Baran et al., 2013).

Another texture extractor, SURF, is reported faster than SIFT. The SURF feature is presented in Baran et al.'s (2013) work on CMM recognition in both non-real time and real time. For the real-time approach, they utilised a SURF descriptor to extract SURF features of CMM in the front view. Then, detected features were stored in an XML file and SVM was implemented to predict CMM in the real-time condition. The accuracy rate of recognition was reported at 91.7 %. Figure 3.8 shows the real time CMMR framework.

For non-real time condition, they used the combination of edge histogram, SIFT, and SURF features in order to have as high classification accuracy as possible, called visual content classification. Next, all features were calculated into numerical values and then stored as binary vectors in an XML file. Last, to classify CMM, the shortest distance of trained CMMs and query image (test image) was measured to predict the CMM class. Figure 3.9 illustrates the CMMR framework for non-real time. They reported the accuracy rate of recognition at 97.2%.

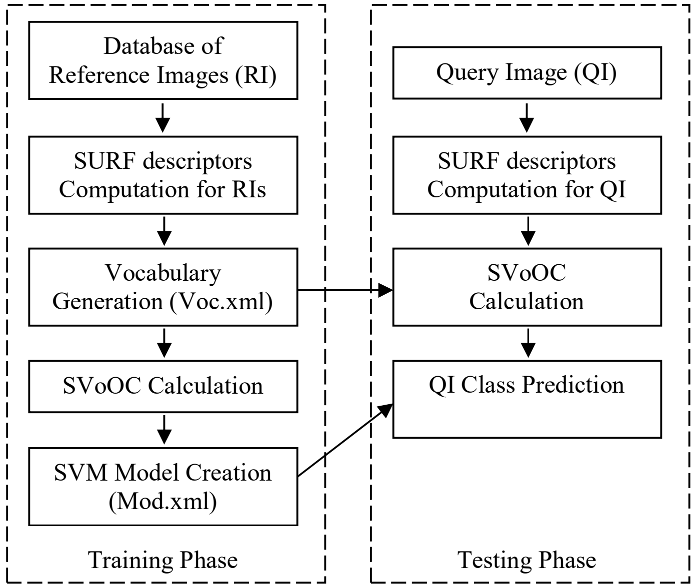


Figure 3.9: Framework of non-real time CMMR approach (Baran et al., 2013).

Furthermore, to improve classification accuracy, Zhang (2013) presented a reliable system for CMM classification that presented the cascade classifier ensembles with reject option. The system consists of two ensemble methods. The first is the ensemble of four classifiers, SVM, k-NN, Random Forest and multiple-layer perceptrons accepting PHOG and Gabor features. The outputs of the first state are accepted class and rejected class. The first ensemble is given in figure 3.10.

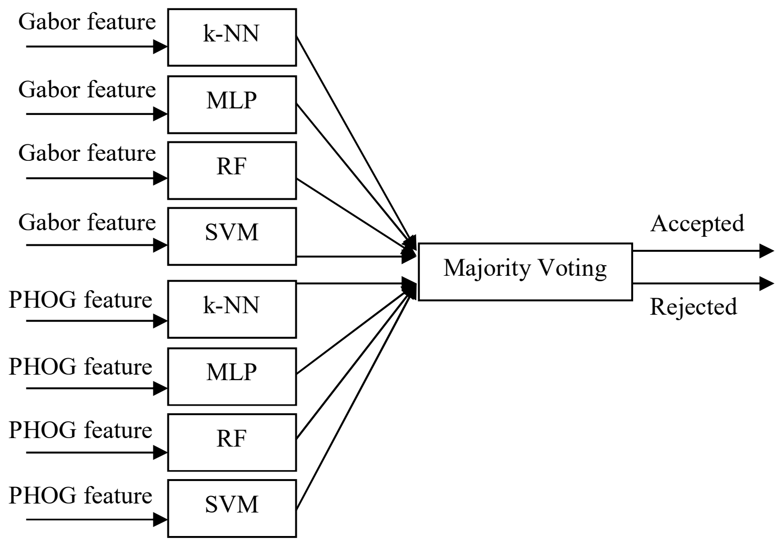


Figure 3.10: Classifier ensemble framework stage 1 (Zhang, 2013).

The rejected class from the first process is sent for verification again in the second ensemble. The second stage is implemented by rotation forest of multiple-layer perceptrons as components to predict the unclassified subject, shown in figure 3.11. This method was reported with 98% accuracy rate among 21 models.

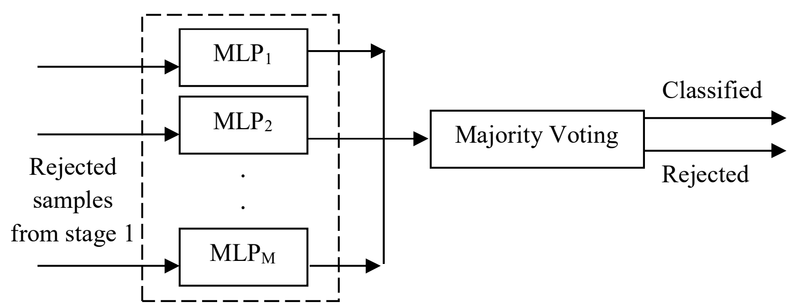


Figure 3.11: Classifier ensemble framework stage 2 (Zhang, 2013).

Another cooperation feature was implemented in Arzani and Jamzad's work (2010). They combined wavelet and contourlet features for CMMR and reported the prediction accuracy tested on 14 CMMs at about 97%.

3.3 CMMR at night

As mentioned in chapter 1, CMMR offers valuable enhancement to support additional information to car identification systems. Even though the recognition rates of existing methods are impressive with more than 90% accuracy, there are some serious drawbacks as most algorithms work well under good lighting conditions and without occlusions. As stated in Raty (2010), most CMMR systems have difficulties at night where many appearances are reduced to headlights, taillights and a few appearances. There are some vehicle recognition works at night, for example, vehicle detection, driver assistance system and vehicle type classification. First, Wang et al. (2005) proposed algorithms to detect street lane and vehicle to assist drivers at night. The method started by detecting lane boundaries by using salient features of lane markers. Then, they extracted taillight spots by adaptive taillight colour thresholds. Finally, they verified the pair of taillights in order to recognise the vehicle. Figure 3.12 shows an example of lane detection and vehicle recognition. Kim et al. (2010) presented a method to detect cars in front by using headlight (HL) and taillight (TL) detection. The method first detected light blobs in a captured image by employing multi-level histogram thresholds. Next, obtained blobs were grouped by a projection-based spatial clustering process. Then, distance and angle of light-blob pairs were estimated to numeric values, as features. Last, in the classification stage, SVM was applied to classify all blob pairs to vehicle HL and TL in order to find car in front positions.

(a) Lane detection (b) Vehicle recognition

Figure 3.12: Lane detection and vehicle recognition (Wang et al., 2005).

Second, Görmer et al. (2009) presented a technique to estimate time before car crash after recognizing in-front vehicles, as driver assistance systems. The technique can be called time to collision (TTC) and figure 3.13 shows the results of a TTC application.

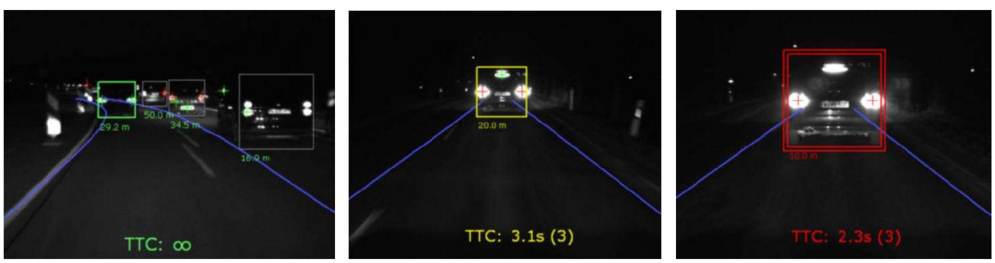


Figure 3.13: TTC application (Görmer et al., 2009).

In addition, rear lamp detection and tracking employing a standard low-cost camera was proposed in O'Malley et al.'s (2010) work. This work optimized the camera configuration for taillight detection and used Kalman filtering to track the rear lamp pair.

Last, vehicle recognition at night is used to classify vehicle type. Gritsch et al. (2009) proposed a vehicle classification system to count car-like and truck-like objects on highways at night by using smart eye traffic data sensor. The algorithm implemented histogram of y-direction of bright spots to detect HL positions. Generally, there are two distinct peak histograms presenting HLs. Then, the distance parameter of HL was used to categorize either car or truck. The results showed that classification error rate at night were less than 6%. In work proposed by Robert (2009), the work aimed to detect, classify and track vehicle in a traffic surveillance system. The algorithm began to locate the vehicle by detecting the headlight pair. Then, headlight and windscreen features were measured and used to distinguish the vehicle class: car or heavy vehicle (bus, truck, coach). Figure 4.14 illustrates an example of a vehicle classification application.

Figure 3.14: Vehicle classification and tracking (Robert, 2009).

3.4 Taillight detection

The current research is dedicated to implementation in limited light or at night. As discussed in chapter 1, at night the straightforward appearances are TL, HL, licence plate and brake lights which can be utilized for CMMR. This section gives an overview, and knowledge and techniques of TL detection processes. Some of them are implemented in this research.

TL detection approaches are presented in many systems in the last decade, such as vehicle detection systems, driver assistance systems (DAS) and vehicle classification systems. First, vehicle detection systems use different kinds of appearances to locate vehicles. Vehicle appearances, for example, colour, shape contour, edges, HL and TL have been proposed to localize vehicles on scenes. TL detection is the popular method used to detect vehicles at night, due to it showing the most salient appearance. Vehicle detection can be implemented in many applications of systems, for instance, monitoring systems, traffic enforcement and management systems. Second, DAS detects HL or TL by front-mounted camera in order to locate the in-front vehicle position. While driving, in-front vehicle detection can help the driver to avoid any vehicle collisions. Last, another advantage of TL detection is to classify the vehicle class, such as sedan, van, bus and truck, by using distance between TLs. This method has been implemented in toll systems and traffic management systems.

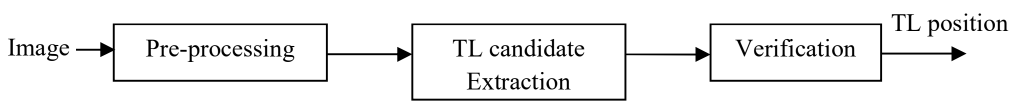


Figure 3.15: TL detection algorithm.

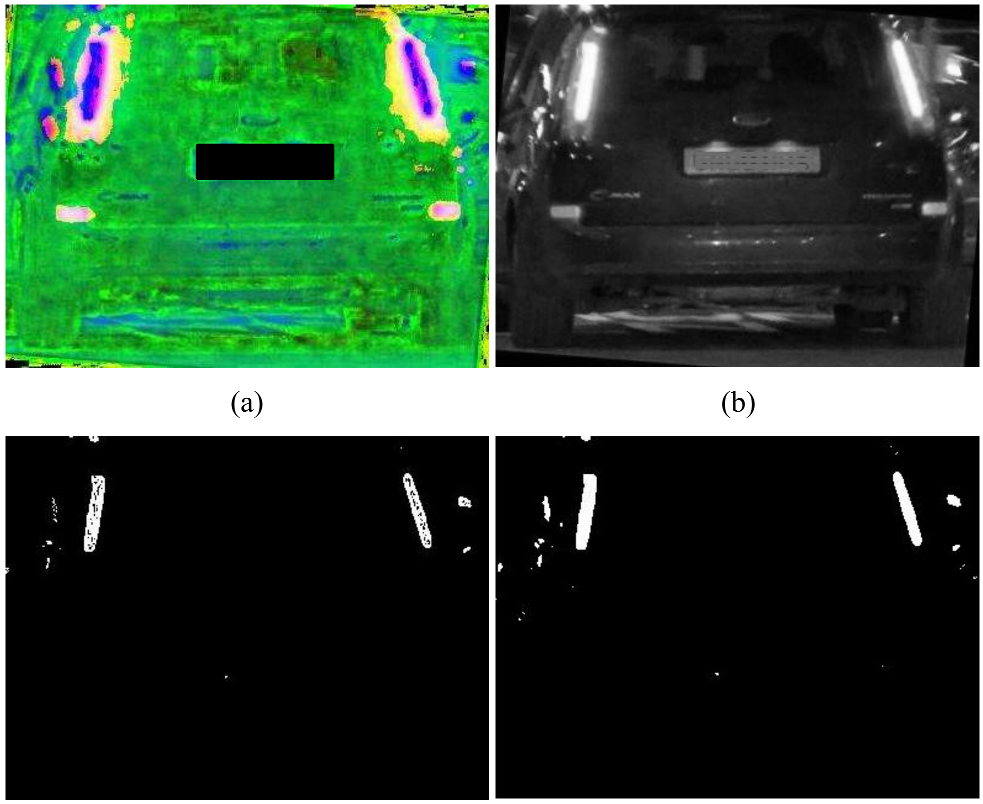
Basically, a TL detection process is comprised of three processes: image pre-processing, TL candidate extraction and TL verification, shown in figure 3.15. First, image pre-processing is the stage to modify image characteristics. Several techniques are applied in this stage, for example, image colour conversion, noise removal and background subtraction. Second, the objective of TL candidate extraction is to segment out potential regions which might include the real TLs. The majority of this technique is a colour-based method (O'Malley et al., 2008). Various colour spaces are used in this step, such as binary, grey levels, RGB and HSV. Last, the verification process aims to choose the real TLs. Salient appearances of TL are used to confirm TL locations, for example, symmetry of TL shape and size (O'Malley et al., 2008) and colour correlation (O'Malley et al., 2010).

Figure 3.16: TL detection. (a) Original image. (b) TL detection (Wang et al., 2005).

The image pre-processing step aims to adjust image properties for a specific problem. Many techniques, for instance, image colour converting, image rotating and image resizing, are used to alter image properties.

Next, TL candidate extraction is the process to extract potential regions from many light sources, such as streetlamps, oncoming HLs and reflections. There are a number of techniques used to extract TL candidates, such as TL shape and colour. Wang et al. (2005) proposed circular shape and aspect ratio to extract TL for a DAS system, shown in figure 3.16. They also combined lane and TL detection processes in order to localize vehicles. The correction of vehicle recognition was reported at about 91%. Another TL candidate extraction method is colour-based. A variety of colour spaces, such as grey, RGB and HSV with various parameters, were used to filter light spots within an image.

First, grey scale colour was proposed to segment bright spots in the work of Chen (2009) and Zhou et al. (2013). However, this method demanded high computational time to localize TLs because sometimes there are many bright spots in a captured image from light sources on roads, for example, streetlamps, signal lights and reflections.



(a) (b) (c) (d)

Figure 3.17: TL candidate extraction steps.

Second, RGB colour space is the most commonly used in TL detection (O'Malley et al., 2008). However, with red, green and blue channels, it is difficult to define the threshold values for TL colours which display a white colour spot surrounded by red colour pixels. A more suitable, natural and practical approach for this problem is Hue-Saturation-Value (HSV) colour space (O'Malley et al., 2008, Li et al., 2012). Figure 3.17 shows examples of TL candidate extraction by applied HSV colour-based method.

Last, TL verification is the process to justify the real TL. The TL verification techniques can be divided into two main methods: rule-based and learning-based. Although learning-based reports a higher detection rate than rule-based, the method requires a training dataset and training time (Ming and Jo, 2011). Another rule-based verification method uses TL physical characteristics to consider final TL position. The majority of rule-based methods are symmetry analysis. TLs are basically placed as a pair and symmetrical with size, shape and position within a vehicle. In Wang et al.'s (2005) study, a vertical position and similar area of bright spots were applied as pairing verification. O'Malley et al. (2008) proposed the symmetry of bright spot alignment, area and aspect ratio. In addition, aspect ratio of bounding box is applied to discard candidate pairs which are too close (near blobs) and too far (other light sources) in rural areas or dark scenes. Another work of O'Malley et al. (2010) implemented colour cross-correlation to verify the TL pair. Symmetry cross-correlation of left and right vehicle parts was evaluated and implemented to localize rear lamps in Li and Yao's (2012) study. In addition, perspective correction was proposed by O'Malley et al. (2011) to solve the symmetry problem of yaw angle of camera, blend road and land change.

3.5 Licence plate detection

Another appearance, licence plate, can be seen or detected at night. This section, therefore, is given to the studies of LP detection which is used in this study's CMMR system. LP detection has been studied as a part of ANPR systems. It is also considered as a crucial process of ANPR systems. If the position of LP has not been localized, it can make a crucial impact on the whole ANPR recognition accuracy. Generally, an LP detection process consists of three processes: image pre-processing, LP candidate extraction and LP verification, shown in figure 3.18.

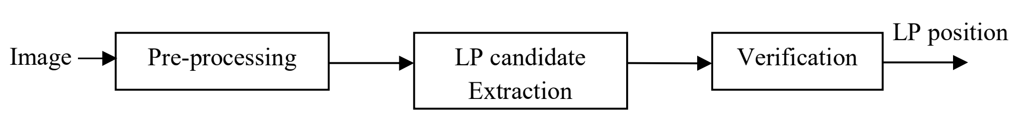


Figure 3.18: LP detection framework.

First, image pre-processing is the process to improve image quality or modify image properties before sending on to the next process. Several methods are used in this step, such as image resizing, rotating, transforming, contrast improving and gray scale converting that are applied to the image depending on the image's problems.

Second, the aim of LP candidate extraction step is to detect the potential regions which might have the real LP. In fact, the salient appearances of a licence plate are colour and characters within the LP having similarity of size. Therefore, colour and edge-based methods are the popular methods to extract a candidate LP. In a colour-based method, LP colour thresholds that depend on the specific country are employed. Figure 3.19(b) shows a binary image filtered by green colour values from original image in figure 3.19(a).

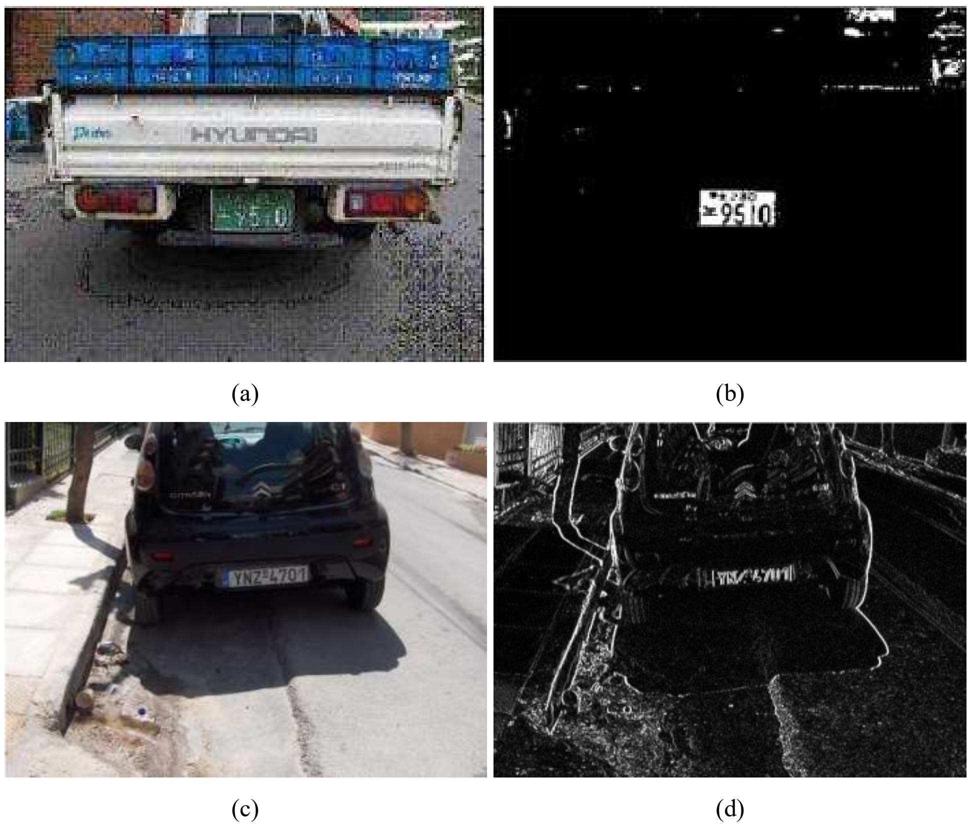


Figure 3.19: LP Candidate extraction. (a, b) Colour detection method (Deb et al., 2009). (c, d) Edge detection method (Mendes et al., 2011).

In edge-based detection, various edge detectors, for example, Canny, Sobel and Prewitt, are used to detect edges and then mathematics morphological operations are applied to connect edge pixels to create regions. Figure 3.19(d) shows a binary image after use vertical edge detection on the image in figure 3.19(c).

Lastly, many LP characteristics are presented to verify the real LP, as follows.

1) LP's rectangular shape is the salient appearance of LP and the characters can be used to localize LP position (Zhang et al., 2005). This technique is the simplest, and a fast and straightforward method, but a problem occurs when the technique is employed in complex scenes having many noise edges.

2) LP's colour is another dominant appearance of LP. Some countries have specific colours and there are common LP colours, such as yellow, white, black and blue. The advantages of this method are the ability to detect inclined and deformed LPs (Chang et al., 2004). Illumination conditions and having LP colour similar to the vehicle body's colour are limitations of this method.

3) Texture of LP is used to locate LP in Anagnostopoulos et al. (2006). This method is reported robust, detecting LP even though the LP boundary is deformed. However, the method has issues when many edges are shown in the object image, which consumes much computation time.

4) LP dimension, width and height, can be utilized to find LP position (Wu et al., 2006). The method is reported straightforward and independent of LP position. The problem of this method is the object image having many regions which have similar LP dimensions.

5) Combining features technique uses two or more features to localize LP position. The method is reported high localization accuracy but time consumed is the limit of this method (Xu et al., 2004).

6) The alphanumeric characteristics within an LP are the appearances having high similarity of size and shape. These features can be used to detect the LP and are reported robust to rotation, as proposed in Matas et al. (2005). The difficulty of this method is when the image has other texts.

CHAPTER 4

PROPOSED CMMR TECHNIQUE

A variety of CMMR techniques are reviewed and discussed in the previous chapter. This chapter presents the proposed CMMR technique under limited lighting conditions at night. The technique is aimed to robustly recognise CMM at night where many appearance features are reduced. Based on CMMR methods in chapter 3, this chapter proposes and describes the algorithm and technique for this CMMR. The proposed method consists of several steps: feature extraction, feature selection and classification process. In the feature extraction process, discriminant features from available appearances of a car image at night are presented in order to have high classification accuracy. Next, the features selected technique is implemented to find dominant features of each car model. The classification process is a step to train the classifier from the features obtained, and then predict new data to predefined classes. Last, predefined features are separated into sub-features depending on the feature detection process. This step aims to simulate if features are missing, as the proposed method should be robust to deal with missing features in real-world situations.

4.1 Proposed CMMR technique

As discussed in previous chapter, CMMR provides more details of a subject car and can improve more confident to the car identification system, as law enforcement system. Most of CMMR works were presented in daytime condition where variety car appearances can be used. At night, car appearances are greatly reduced making existing CMMR techniques do not fully satisfy in this condition because available appearances are limited or different. Therefore, this research aims to solve problem of CMMR at night. The proposed CMMR technique is based- on state-of- the-art of pattern recognition system which consists of image processing, feature extraction and classification.

Traditionally, there are two categories of classification technique. First, multi-class classification is the method to classify new data into one of more than two classes. The second classification method is single class classification classifying instance into one of two classes which can be called binary classification. The proposed research aims to classify car make and model of interest as a target out of other models, as shown in figure 4.1. This classification strategy can be used in real world application. For example, if a scene from a CCTV camera consists of four different types of vehicle, 2011 Kia Sportage, 2012 Skoda Yeti, 2016 Volvo XC90 and 2015 Audi Q7. If a suspected car is a 2011 Kia Sportage, the proposed method aims to detect only that particular make and model, classifying the vehicles in the scene as a 2011 Kia Sportage and 'non' 2011 Kia Sportage. Since only the Kia (target class) is the car of interest, there is no need to classify or detect the rest of the makes and models. Therefore, a binary classification technique is required to identify a target class, instead of a multi-class classification which unnecessarily involves more complex algorithms, data base and computational workload.

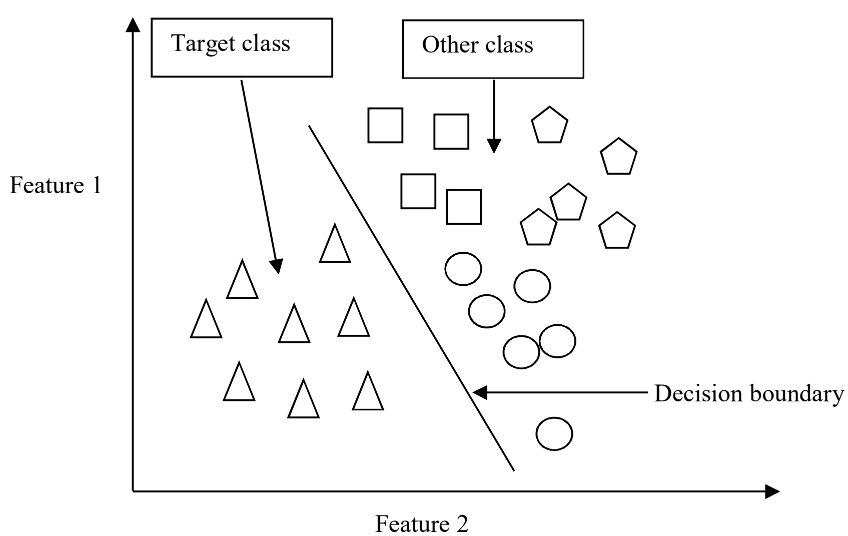


Figure 4.1: Binary classification diagram for target car model recognition.

The classification technique has three sub-processes, image processing, features extraction and classification process. First, image processing is a method to adjust or improve image characteristics in order to incorporate to the next process and defined parameters. The research detects taillight positions and licence plate in order to have car's features. In taillight detection, the process is based on colour method which uses HSV colour space to detect candidate taillights and decides the real taillights by the most symmetry score of taillight candidate pairs. In addition, licence plate, technique, is detected by applying edge-based algorithm and licence plate dimension thresholds. Grey level colour is the most suitable colour for edge detection technique. Therefore, image manipulation is needed to adjust image and improve image characteristics in order to suitable to designed algorithm. There are four image manipulation techniques such as image rotation, image resizing, colour conversion and contrast enhancement. This particular research is focused only on solving the problem of CMMR at night. The technique defines car's appearances and then develops the most suitable classification technique to be used for this condition. Therefore, at this stage, the image manipulation part of the process is manually conducted. It is intended to be the proof-of-concept stage for the proposed CMMR method. The full automatic process can be implemented in the future.

As mentioned, image manipulations are manually implemented on original image which consist of image resizing, rotating, colour conversion and contrast enhancement techniques. Image resizing, colour conversion and contrast enhancement are not making any impact on overall performance by users because the algorithms are applied using pre-defined parameters (fixed parameters), for example, image is resized to the fixed dimension of 800×600 pixels and image is converted to HSV colour space, in the taillight detection step. However, manual image rotation is affected by users. For example, inexperienced users may perform manually image rotation that might lead to image (TL positions) asymmetry affecting classification accuracy.

(a) (b)

Figure 4.2: Example images of car front and rear view

Second, feature extraction is a process to determine distinguishable features from car image to classify car make and model. Car features can be either obtained in front and rear views. At night, headlights tend to be on and if images are taken in the front of car or against headlight, the obtained car images are blurred and glared which can be seen in figure 4.2(a). On the other hand, there is less blur and glare when capturing image in rear view, as shown in figure 4.2(b). In rear view, it can be seen that the dominant appearances are taillight shape and licence plate position that can be utilised, as car features, to recognise car make and model. Therefore, this research decides to use car rear view to classify car make and model.

Last, classification process is the method to classify new data into a predefined class. In the literature, many classifiers and classification techniques have been presented to classify car makes and models. For example, support vector machine (SVM), decision tree (DT) and k-nearest neighbour (kNN), Naïve Bayes, variety of neural networks techniques and ensemble methods were used in previous CMMR works. From initial experiments, given the types and characteristics of the features of interest in this particular project, SVM, k-NN and DT are shown to be the most suitable classifiers under the circumstances. The majority vote method is then applied to finally decide the final classification result. In the experiments, SVM produced high classification accuracy with the trained dataset. Figure 4.3

shows an example of car's feature space classified by SVM classifier. It can be seen that SVM produced a good classification, separating the data into two groups. In addition, SVM was reported the highest classification accuracy on artificial dataset if optimum parameters are implemented (Amancio et al., 2014). Moreover, it commonly classifies data into two classes that is suitable to the proposed classification strategy. Secondly, K-NN was shown the second highest classification accuracy from the study of Amancio et al. (2014) and k-NN has only one parameter, number of neighbour, which will consume a few computation times and easy to implement in real world applications. Last, DT which is the most popular method in data mining researches (Kotsiantis, 2008) and mostly used in binary classification problems is selected. Furthermore, DT can reduce the classification error by apply pruning technique. Other techniques were not considered because of many parameters used such as neural networks techniques and worst classification performance, Naïve Bayes.

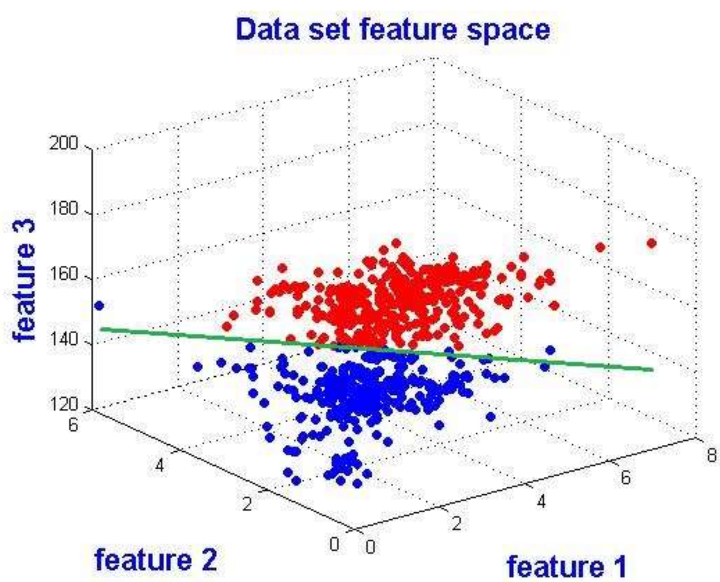


Figure 4.3: Example feature space applied by SVM classifier

The "no free lunch" theorem of Wolpert and Macready (1997) states that there is no best single classifier in any classification problem (domain). Each classifier may have its own region in the feature space where it performs the best (Jain et al., 2000). It has been proven that the classification accuracy can be improved by using an ensemble of classifiers (Dougherty, 2013). In this research, therefore, classifier ensemble (majority vote) is employed in the classification stage. The ensemble contains with various individual classifiers: support vector machine (SVM), decision tree (DT) and k-nearest neighbour (kNN). They are different in their decision making and can complement the weaknesses of each other in order to increase classification accuracy and will generalise on future data.

The proposed CMMR system is shown in figure 4.4. The system consists of two processes: training and identification (classification) and both processes operate in similar steps: image pre-processing, feature extraction and classification. As given in figure 4.4, in the training process, target car images are input to the pre-processing stage which will adjust image characteristics to be suitable for the next process. Then, design features are extracted from the object image. The feature extraction process includes several steps: Licence Plate (LP) detection, Taillights (TL) detection and feature extraction. After that, feature subset selection is applied in order to find dominant features for the most distinguishable features of a particular target model. Last, the target car model is trained by the classifier and then stored in a database. In the classification process, which is done in real time, a stream of images from CCTV containing different car models is considered. The optimal feature set and the trained classifier for the particular target car model are applied to these images to identify that particular CMM. In following sections give more details of each process.

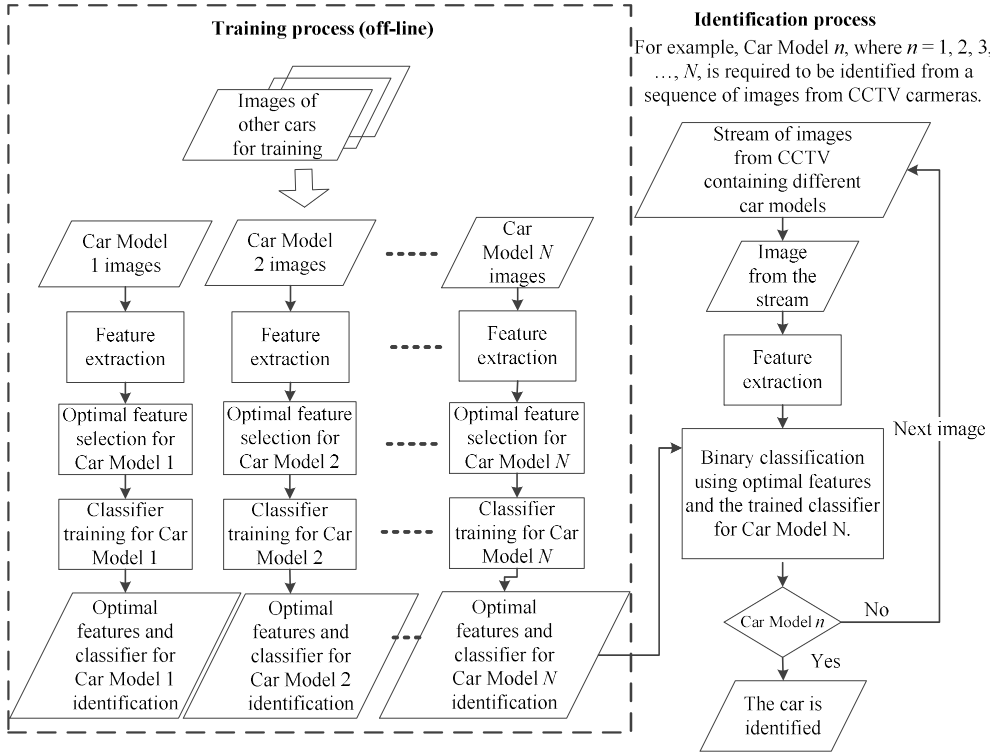


Figure 4.4: Overview of proposed CMMR system.

4.2 Image pre-processing

In real-world applications, captured images might not be suitable for the technique designed. The images will be affected by illumination variations, occlusions and complex backgrounds. Therefore, image pre-processing techniques have to be applied to adjust image properties to approximate the research's predefined parameters and algorithms. Various techniques are implemented in this step, for example, image rotation, resizing, colour conversion and contrast enhancement.

4.2.1 Image rotation

Car images can be captured from different views in real applications. The system presented uses an un-skewed image of the car rear view to recognise CMMs and furthermore, symmetric measurement is utilized to verify TL pair position in the TL detection process. Therefore, the image needs to undergo image rotation in order to have a symmetrical car image. In the proposed system, manual rotation is utilised until the image is symmetrical. The image is rotated clockwise if it was captured on the left-side of the road, otherwise counter-clockwise if captured on the right-side. In the experiments, images taken on the left-side of a street were manually rotated clockwise by 1 degree until symmetrical, up to a total of five degrees. Figure 4.5(b) shows an example of a clockwise-rotated image of the original image in 4.5(a).

(a) (b)

Figure 4.5: Example car image rotation. (a) Original image. (b) Rotated image.

4.2.2 Image colour conversion

As mentioned in the previous section, LP and TL positions are detected in order to have features of the CMM in the rear view. In the LP detection process, an edge-based method is employed and a grey-level image is reported more appropriate than RBG in edge extraction (Mendes et al., 2011). Thus, grey colour conversion is implemented in the work to convert the RGB to grey colour image, as shown figure 4.6(a) and (b), respectively. For the TL detection process, TL colour is basically white (bright) in the centre and surrounded by red colour. HSV colour space seems to be more suitable than RGB, as it can better define parameters for those TL colours (O'Malley et al., 2008). In the TL detection stage, the image is converted to HSV colour space. Figure 4.6(c) shows the HSV colour image converted from the RGB image.

(a) (b) (c)

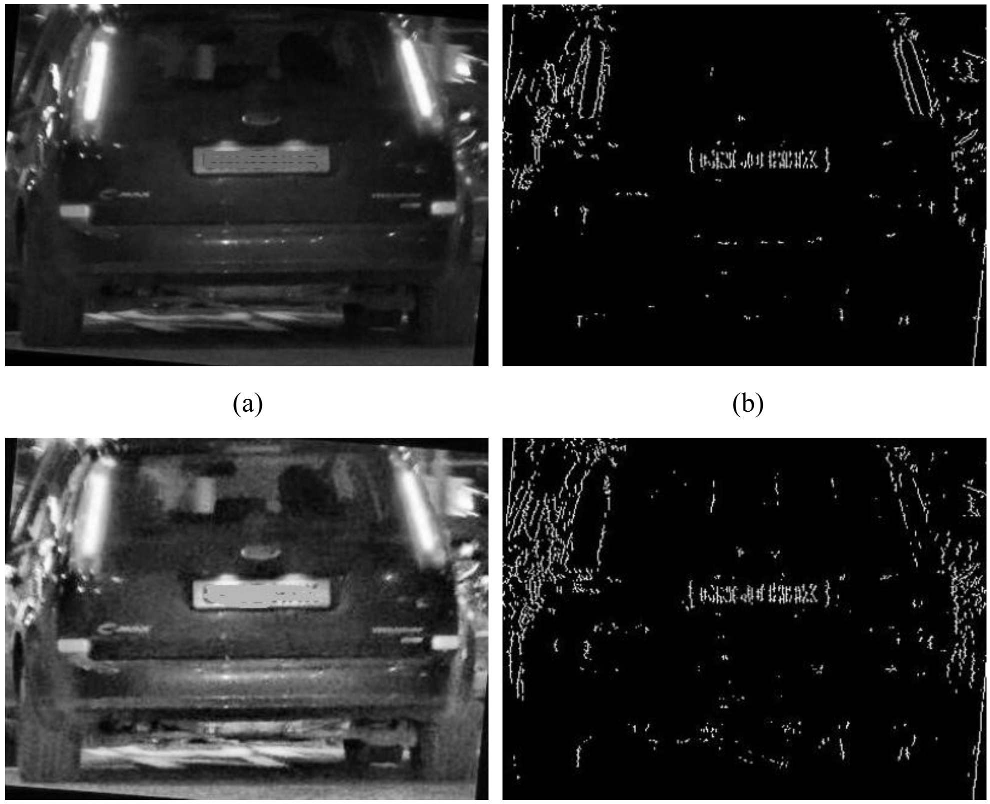
Figure 4.6: Image colour conversion a) Original image. b) Grey image. c) HSV colour image.

4.2.3 Image resizing

Image resizing is aimed to re-scale the image to work with the designed parameters (thresholds) of the presented technique. In the LP detection step, the proposed technique uses an edge-based technique that defines many threshold values (LP dimensions) to create LP candidate regions. Then, image resizing is applied on the object image. Furthermore, the large image dimensions might lead to slow execution times. In the technique, images are resized to 800×600 pixels, which are associated with the predefined parameters.

4.2.4 Contrast enhancement

This research aims for implementation under limited lighting conditions at night when many appearances, such as car texture, edge and shape contour might be faded. Moreover, there is some interference from other light sources which will make regions of interest appearances too bright causing its low contrast. Then, to improve the detection rate, a contrast enhancement method is employed if a subject image has low contrast. The contrast improvement techniques, histogram equalization and adaptive histogram equalization, are implemented in the LP detection process. Figure 4.7(b) shows the edge image of original image figure 4.7(a). Figure 4.5(d) gives the edge image of the contrast improvement image of figure 4.7(c). Obviously, many more edges can be seen in figure 4.7(d) than in figure 4.7(b).



(a) (b)

(c) (d)

Figure 4.7: Contrast enhancement images and edge images.

4.3 Feature extraction

The goal of this process is to obtain CMM characteristic properties or parameters. Then, these parameters are measured to numeric values and then used to learn and classify CMMs. The majority of previous works recognise CMM in front view in daytime, when many kinds of features can be used. However, at night or under limited lighting conditions, car front headlights tend to be on. Due to brightness and glare of headlights, most important features captured using the front view are, therefore, blurred or incomplete resulting in serious recognition inaccuracy. Figure 4.2(a) shows an example image captured in front view and many appearances, such as texture, corners and edges, are darkened. Furthermore, there are reflections occurring from other light sources. Figure 4.2(b) shows a car image in rear view; and obviously salient features, such as taillight shape, distance and angle between taillight and licence plate, can be obtained. Rear view appearances have been used to classify vehicle type such as sedan, truck, van and unknown model and reported high classification accuracy (Kafai and Bhanu, 2012). Then, the proposed method designs to use these appearances as measured features to classify CMM. From observation, a car model has unique taillight shape, size and distance between taillight and licence plate. In addition, the relative angle of TL and LP is generally distinctive for each CMM. In order to obtain these features, there are three sub steps: LP localization, TL detection and feature extraction.

4.3.1 LP localization

The aim of this stage is to detect LP position in order to have its size and shape so that can be used to normalize the features. LP localization techniques have been studied in many researches. In fact, dominant appearances of LP are colour, texture, rectangular boundary and containing alphanumeric characters. Therefore, previous researches have used these appearances to localize LP position. During daytime, texture and colour feature based methods produce high detection rates because most features are clearly presented in the scene. At night, a number of features are greatly reduced due to low illumination. Moreover, colour feature is interfered with and changed due to the lighting conditions in the area and reflections from other vehicles' lights.

The method proposed in this work employs the LP detection technique developed by Mendes et al. (2011), shown in figure 4.8. The technique detects an LP by using an edge-based feature which is reported to be a simple, fast and straightforward algorithm. From the experimental results using a database of 722 images, a high detection rate of 95.43% has been achieved. Moreover, the technique demonstrates robustness in coping with various illumination conditions. The algorithm has two main stages: LP candidate extraction and LP verification.

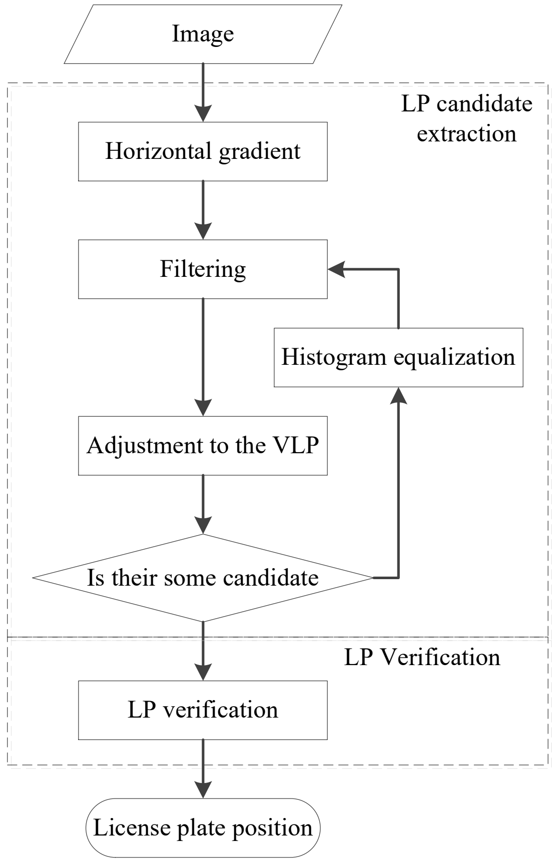


Figure 4.8: Licence plate localization algorithm (Mendes et al., 2011).

1) LP candidate extraction

This process aims to obtain LP candidate regions through these steps: image pre-processing, edge detection, filter functions applied, mathematical morphological operations, and binary image conversion.

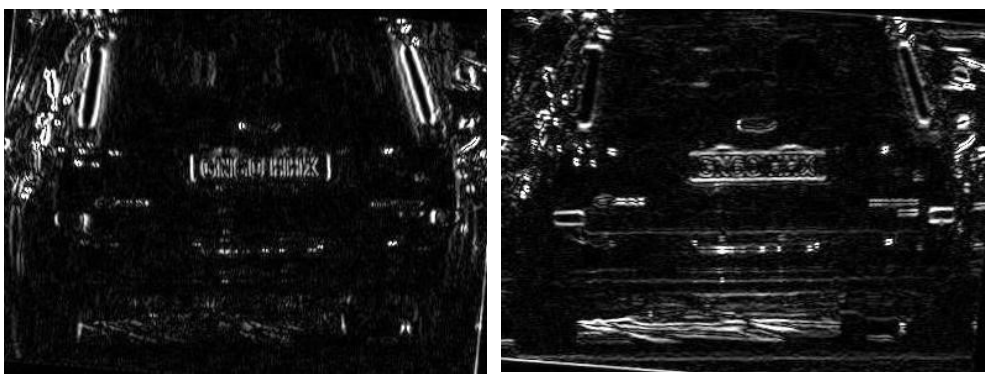
A. Image pre-processing

The first task is to reduce the object image size to 640×480 pixels. Image resizing is applied to adjust image resolution to an appropriate size suitable to the predefined thresholds. In addition, the original size of images, 1920×1080 pixels, is large and might require expensive computational time.

B. Edge detection

Generally, an LP contains alphanumeric characters which can be utilized to locate the LP position. To find the characters within the image in order to detect the LP, edge detection is implemented and a region with high edge density is considered as the LP position. The algorithm first converts the image to grey scale in order to support the edge-based method and contrast enhancement technique. Then, Sobel vertical edge detection is applied to extract vertical edges.

From the study of Bai and Liu (2004), vertical edge detection obtains less noise than horizontal edge detection. Furthermore, vertical edges can be merged to build the LP region. Figure 4.9 shows an example of vertical and horizontal edge detection.

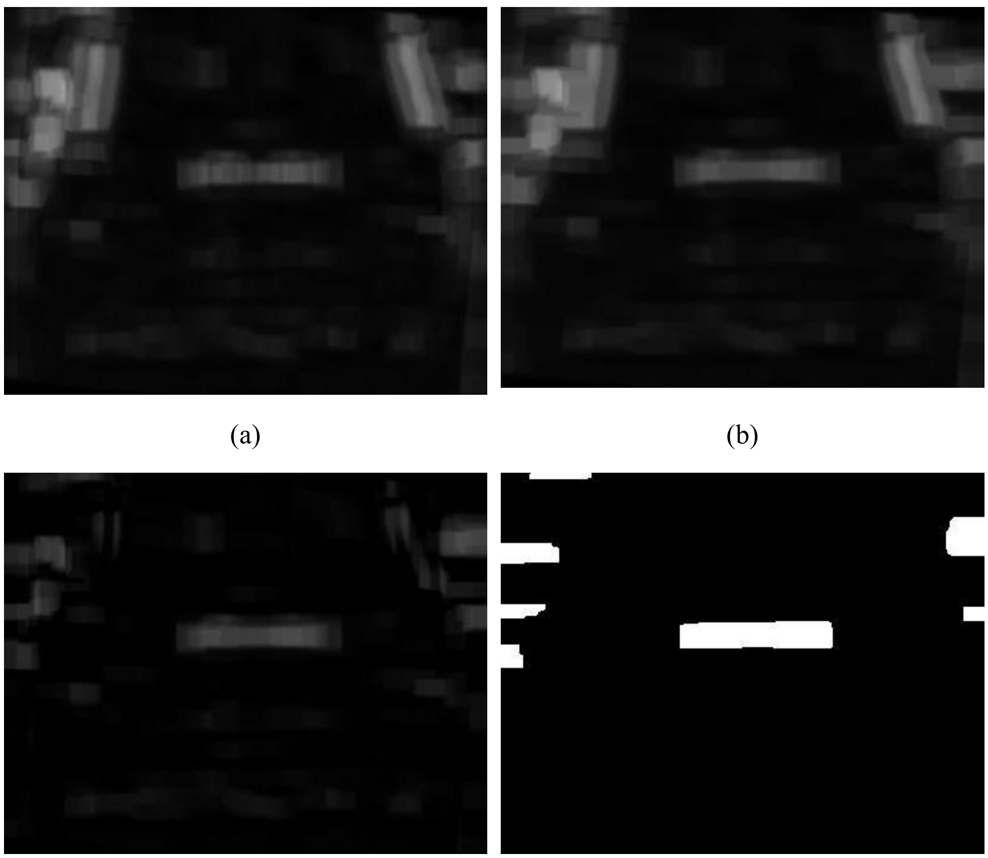


(a) (b)

Figure 4.9: Edge detection of car image. (a) Vertical edge detection. (b) Horizontal edge detection.

C. Morphological operations

The goal of morphological operations is to manipulate the edge image in order to create the LP region. First, a mean filter is applied to the image to emphasise the LP region and to build the LP region. The filter dimension is a $w \times h$ rectangle where w and h are the expected LP width and height, respectively. Figure 4.10(a) illustrates an image with mean filtering applied. Then, noise and small regions are removed by applying a morphology opening operation with structure element (SE) size equal to minimum character height (Mendes et al., 2011), given in figure 4.10(b). After that, large regions are eliminated by implementing an opening operation with a column SE size of the maximum character height to gain effective regions (Mendes et al., 2011) which can be seen in figure 4.10(c). Last, the filtered image is converted to a binary image (Mendes et al., 2011), to which the threshold value is automatically given by applying Otsu's method (Otsu, 1979), figure 4.10(d).



(a) (b)

(c) (d)

Figure 4.10: LP candidate extraction steps.

2) LP Verification

The aim of this step is to verify the real LP among the candidate regions. The potential candidates are preserved by following these characteristics: 1) its width is greater than its height, 2) its width and height are larger than the thresholds, and 3) the LP cannot touch the image boundary (Mendes et al., 2011). Table 4.1 shows candidate filter constraints. Figure 4.11(a) illustrates the potential candidate regions.

As explained in the beginning of the section, an LP contains alphanumeric characters whose colour is different from the background. This property can be used to localize the LP by implementing probability distribution of intensity value.

Table 4.1: Candidate region constraints

No.	Constraint	Description
1	$w > h$	The standard licence plate has a width larger than its height.
2	$w >$ threshold $h >$ threshold	Licence plate dimensions should greater than defined thresholds, such as w=120 and h=25 pixels.
3	LP ≠ image boundary	Licence plate should not be located on an image boundary.

The research uses the coefficient of variation to measure the candidate's grey scale distribution. The largest grey scale distribution is considered as the LP. The coefficient variation (CV) is defined as:

$$\mathrm{CV} = \frac{\sigma}{\mu} \tag{4.1}$$

where μ and σ stand for mean and standard deviation of pixel values within the candidate region. Figure 4.11(b) shows an image of LP localization.

(a) (b)

Figure 4.11: (a) Potential candidate regions. (b) LP localization.

4.3.2 TL detection

The objective of this stage is to detect taillights in order to have their size, shape and position measured as features. TL detection approaches have been presented in many studies in the last decade, such as vehicle detection, driver assistance system (DAS) and vehicle classification (Gritsch et al., 2009). In this paper, the algorithm presented by Boonsim and Simant (2014), with accuracy of 95.35%, is used to localize TL positions. The algorithm has two main steps candidate extraction and TL verification. Figure 4.12 shows the taillight detection algorithm.

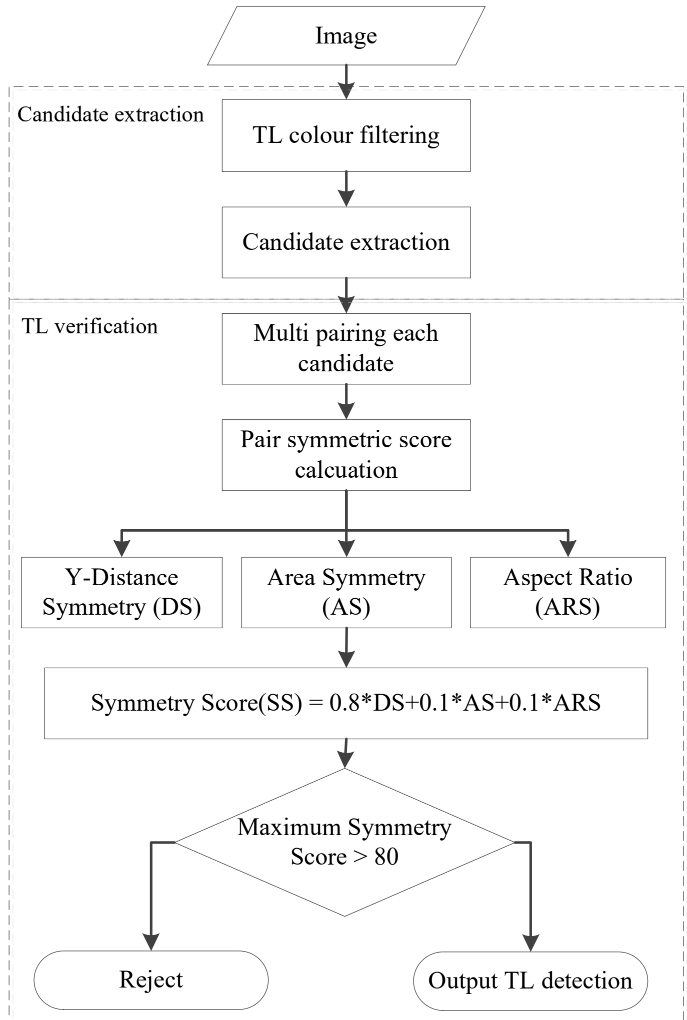


Figure 4.12: Algorithm of taillight detection (Boonsim and Simant, 2014).

1) TL candidate extraction

TL candidate extraction is the process to gain TL candidate regions consisting of these steps: TL colour filtering, image intersection, noise or small regions removal and candidate extraction.

A. TL colour filtering

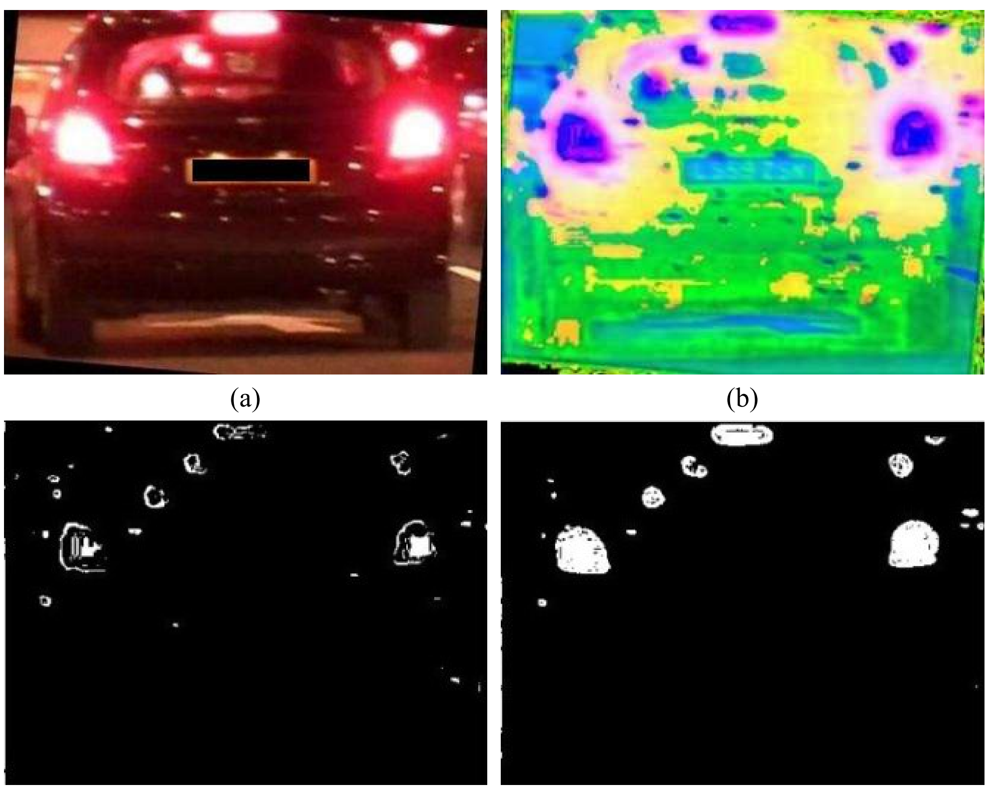
A colour-based method is commonly used to extract taillight candidate regions. Basically, taillight colour is white in the centre and surrounded by red colour

(O'Malley et al., 2008). In a colour-based technique, TL colour thresholds are implemented in order to filter out TL colour pixels. With the TL colour, HSV colour space, which is reported more appropriate to TL colour than RGB colour, is used in this research (O'Malley et al., 2008).

Table 4.2: TL Colour thresholds (O'Malley et al., 2008)

	Hue	Saturation	Value
Red	340°–30°	0–30	80–100
White	All	0–20	99–100

First, the RGB image is converted to HSV colour space, which is illustrated in figure 4.13(b), converting the original RGB image in figure 4.13(a). Red and white colour thresholds, shown in table 4.2, are employed to detect TL colours. Figures 4.13(c) and 4.13(d) show the binary image from filtering red and white colour pixels, respectively, of the HSV image in figure 4.13(b).

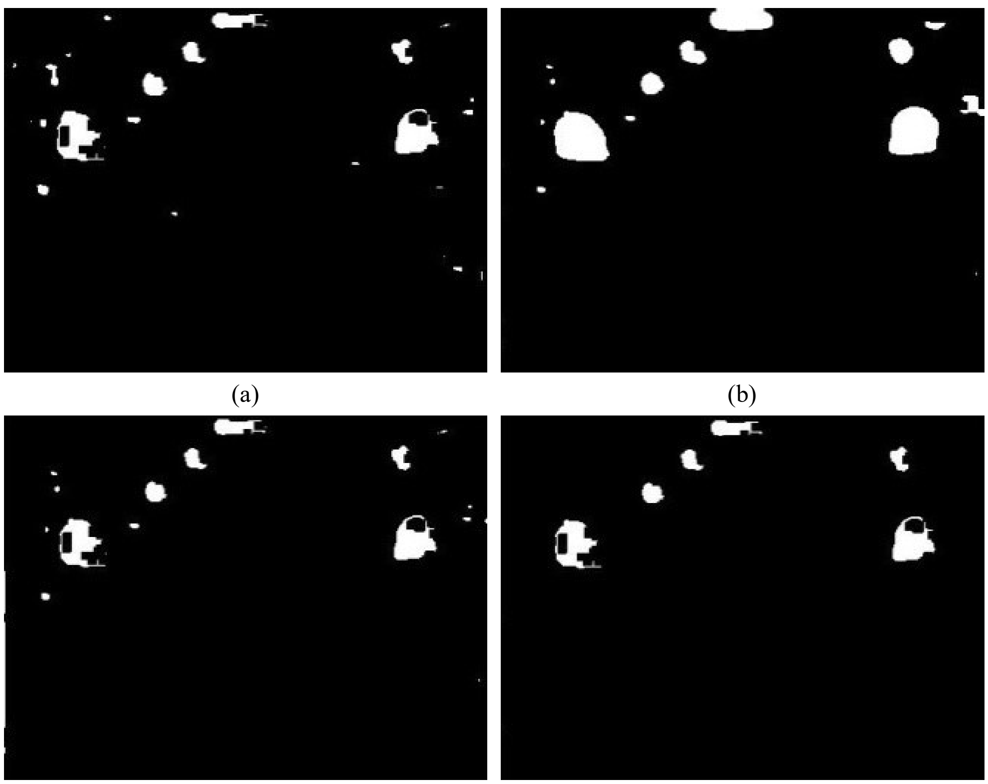


(a) (b) (c) (d)

Figure 4.13: TL colour filtering steps.

B. Candidate extraction

From the previous step, binary images of red and white pixels are obtained. To create the TL candidate regions, first, morphological operations are implemented on each binary image to merge closed pixels in order to have regions, which are shown in figures 4.14(a, b). Then, TL candidates are extracted from red regions containing white regions by applying image intersection, illustrated in figure 4.14(c). Last, small regions under the threshold (50 pixels) are removed as filtering potential regions, displayed in figure 4.14(d).



(a) (b)

(c) (d)

Figure 4.14: Images of mathematical morphological operations.

2) TL verification

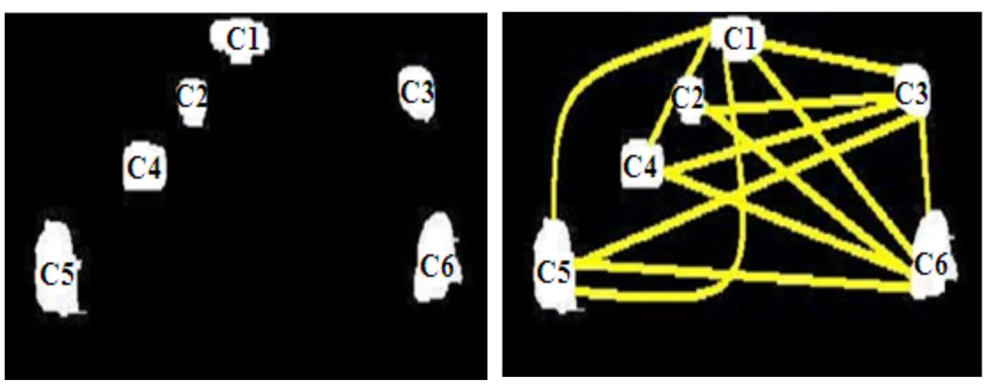
Basically, TLs are similar in size, shape and position on a vehicle. Therefore, to confirm the TL positions, symmetry evaluation of those properties is applied. A number of steps are employed in this stage. First, each candidate region is multi-paired to other candidates as a TL couple and then symmetry analysis of position, size and shape are calculated for each pair. Last, the highest symmetry score is used to verify the TL positions.

A. Candidate pairing

Connected component analysis (CCA) is firstly applied to label each candidate in order to have their characteristic parameters. Then, candidates are named as C_i where i=1, 2, 3..n, which is shown in figure 4.15(a). After that, each candidate is multi-paired with the others as shown in figure 4.15(b). Last, a number of pairs P_k are obtained after pairing in equation 4.2:

$$P_k = (C_i, C_j) \tag{4.2}$$

where k represents a number of pairs and i, j are defined as the number of candidates C where i is not equal to j ($i \neq j$). For $P_k = (C_i, C_j)$ and pair $P_{k+1} = (C_j, C_i)$, these pairs are defined as the same pair which can be denoted by $P_k = (C_i, C_j) = (C_j, C_i)$.



(a) (b)

Figure 4.15: Candidate pairing. (a) Candidate naming. (b) Multi-candidate pairing.

B. Symmetry analysis

The symmetry scores of size (area), shape (aspect ratio) and position (y-axis distance) are calculated to check the similarity of each pair. First, the symmetry of position is considered by estimating y-direction distance of each pair. *Y*-axis direction distance is the length between border and centre of candidates in *Y*-axis and the direction symmetry score of the pair can be computed by equation 4.3 where *DS* is *Y*-axis distance symmetry score of pair P_k. H_i and H_j are the *Y*-axis distance between border and centre of C_i and C_j, respectively.

$$DS(P_k) = \left(1 - \frac{|H_i - H_j|}{H_i + H_j}\right) \times 100 \tag{4.3}$$

Next, size symmetry is checked by using equation 4.4 to justify area characteristic equality where *AS* is defined as area (size) symmetry score of pair P_k. A_i and A_j are the areas of candidates C_i and C_j, respectively.

$$AS(P_k) = \left(1 - \frac{|A_i - A_j|}{A_i + A_j}\right) \times 100 \tag{4.4}$$

Then, the symmetry of shape is examined by analysing aspect ratio of candidate width and height is implemented by equation 4.5 where *ARS* is the aspect ratio symmetry score of pair P_k. ARS_i and ARS_j represent the aspect ratios of candidates C_i and C_j, respectively.

$$ARS(P_k) = \left(1 - \frac{|ARS_i - ARS_j|}{ARS_i + AR\ _j}\right) \times 100 \tag{4.5}$$

Last, the pair aspect ratio is checked. The aspect ratio of TL pair should have more than 3 and less than 8 (O’Malley et al. 2008) as threshold values. If the aspect ratio of the candidate pairs is not within the thresholds, it is discarded. A pair aspect ratio can be computed by equation 4.6.

$$Pair\ Aspect\ Ratio\ (P_k) = \frac{Distance(C_i, C_j)}{Average\ width\ of\ two\ taillight} \quad (4.6)$$

C. TL Verification

The highest symmetry score is used to decide the final positions of the TLs. The total symmetry score is calculated by the symmetry score equation in equation 4.7 with associated weight values. Due to some complex scenes, there are many candidates having the high symmetry size and shape that could produce incorrect TL detection. Thus, position symmetry score is experimentally defined as the most significant value followed by size and shape symmetry. The research sets weight values as 0.8, 0.1 and 0.1 for *DS*, *AS* and *ARS*, respectively.

$$\text{Symmetry Score (SS)}_k = 0.8*DS_k + 0.1*AS_k + 0.1*ARS_k \quad (4.7)$$

Finally, the maximum symmetry score is considered to confirm the position of TLs. Figure 4.16 illustrates an example image of TL detection. The symmetry score of TL should be more than 80, as in equation 4.8. If the score is less than the threshold value, the test images are discarded.

$$\text{TL pair} = \text{Maximum (Symmetry Score } (P_k)) > 80 \quad (4.8)$$

Figure 4.16: TL detection image.

4.3.3 Feature extraction

Once a vehicle's LP and TLs are identified, a number of important features, such as dimensions, distances and angles between LP and TLs, can be derived, as shown in figure 4.17. In the figure, *H*, *W* and *C* are expected TL and LP heights, width and centre point, respectively, and the numbers 1, 2 and 3 indicate left-TL, right-TL and LP, respectively.

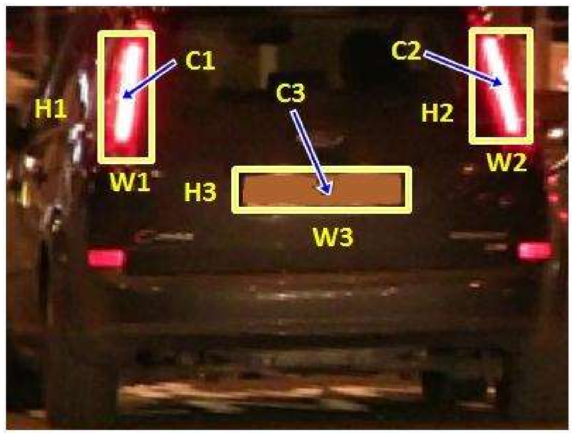


Figure 4.17: TL and LP detection and geographical measurement.

Those features are divided into two types: geographical features, given in table 4.3, and TL shape features. The aspect ratio features are used because they are normalized features and do not depend on the vehicle's size in the image. The features are extracted from the car rear view, which contains features of left and right taillights because the licence plate is not located in the centre of the car in some CMMs. Thus, the features of left and right taillights to licence plate are different.

Table 4.3: List of geographical features.

1)	Aspect ratio of left-TL
2)	Aspect ratio of right-TL
3)	Aspect ratio of left-TL width and LP width
4)	Aspect ratio of left-TL height and LP height
5)	Aspect ratio of right-TL width and LP width
6)	Aspect ratio of right-TL height and LP height
7)	Angle of left-TL and LP
8)	Angle of right-TL and LP
9)	Distance between TLs per LP width
10)	Distance between left-TL and LP per LP height
11)	Distance between right-TL and LP per LP height
12)	Distance between TLs per average of TL width

1) Aspect ratio of TL shape

The aspect ratio of TL shape (AR_TL) is the proportion of TL width to TL height that can be calculated according to equation 4.9. For example, the aspect ratio of taillight in figure 4.18 is calculated as *W1*/*H1*.

$$\text{AR\_TL} = \frac{\text{Taillight width}}{\text{Taillight height}} \quad (4.9)$$

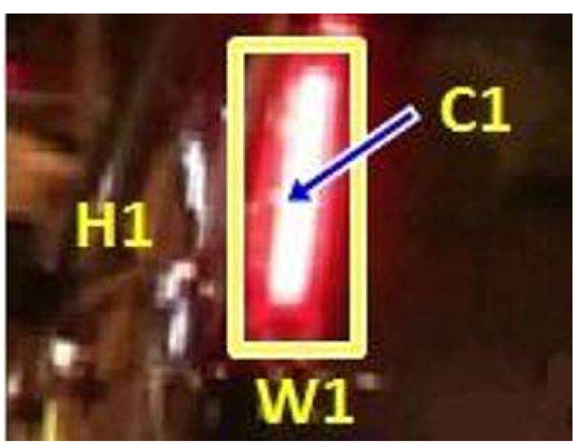


Figure 4.18: TL dimensions

2) Aspect ratio of TL and LP width

The aspect ratio of TL and LP width (AR_TL-LP_W) is the ratio of TL width to LP width, which can be computed by equation 4.10. For example, this value in figure 4.17 is computed as *W1*/*W3* or *W2*/*W3*.

$$\text{AR\_TL-LP\_W} = \frac{\text{Taillight width}}{\text{Licence plate width}} \tag{4.10}$$

3) Aspect ratio of TL and LP height

The aspect ratio of TL and LP height (AR_TL-LP_H) is the proportion of TL height to LP height, which can be measured according to equation .11. For example, the feature in figure 4.17 is calculated as *H1*/*H3* or *H2*/*H3*.

$$\text{AR\_TL-LP\_H} = \frac{\text{Taillight height}}{\text{Licence plate height}} \tag{4.11}$$

4) Angle of TL and LP

The angle of TL and LP can be measured by the LP centre point to the centre of a TL. The angle of LP and TL is defined by equation 4.12. Figure 4.19 shows how to find the angle between the LP and left TL.

$$\text{Cos}\ \theta = \frac{V_1+V_2}{|V_1||V_2|}$$

$$\text{Cos}\ \theta = \frac{u_1v_1+u_2v_2}{\sqrt{{u_1}^2+{u_2}^2}\cdot\sqrt{{v_1}^2+{v_2}^2}}$$

$$\theta = \text{acos}\left(\frac{u_1v_1+u_2v_2}{\sqrt{{u_1}^2+{u_2}^2}\cdot\sqrt{{v_1}^2+{v_2}^2}}\right) \tag{4.12}$$

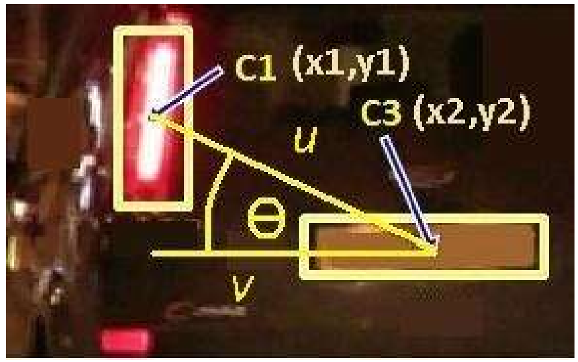


Figure 4.19: Measurement of angle of TL and LP.

5) Aspect ratio of distance between TLs with LP width

The aspect ratio of the distance between taillights with LP width (AR_Dist-TL-LP-W) can be calculated according to equation 4.13. For example, this value in figure 4.20 is computed as Dist. (*C1*, *C2*)/ *W3*.

$$\text{AR\_Dist-TL-LP-W} = \frac{\text{Dist.}(C_i, C_i)}{\text{Licence plate width}} \tag{4.13}$$

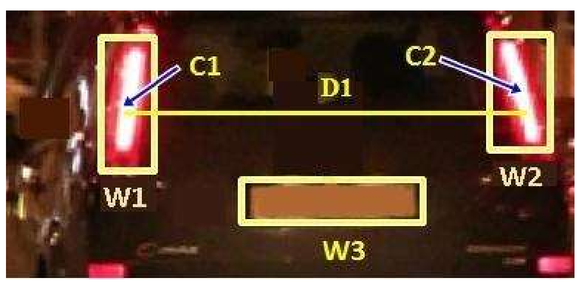


Figure 4.20: Distance between taillights measurement.

6) Aspect ratio of distance between TLs with TL width

This feature is the ratio of the distance between taillights with the average of TL width (AR_Dist-TL-TL-W), which can be estimated by equation 4.14. For example, the value in figure 4.20 is calculated as Dist.(*C1*, *C2*) / Avg.(*W1*,*W2*).

$$\text{AR\_Dist\_TLs\_TL\_W} = \frac{\text{Dist.}(C_i,C_i)}{\text{Avg.}(W_i,W_j)} \tag{4.14}$$

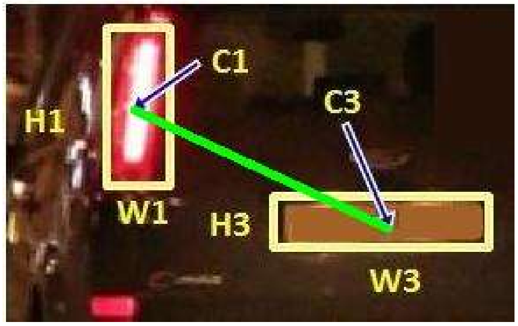


Figure 4.21: Distance between taillight and LP.

7) Distance between TL and LP with LP height

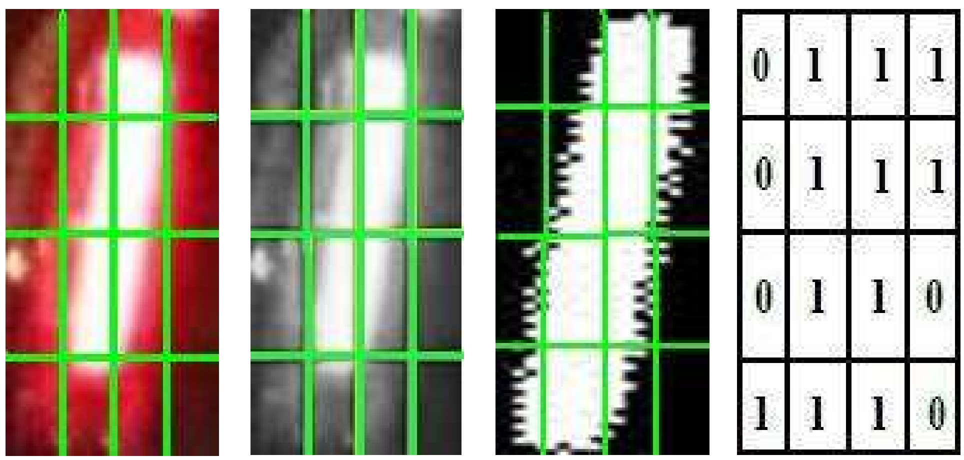
This feature can be calculated according to equation 4.15. For example, the aspect ratio of distance between taillight and LP with LP-height in figure 4.21 is calculated as (*D2*/*H3*) or (*D3*/*H3*).

$$\text{AR\_Dist-TL-LP-H} = \frac{\text{Distance of TL and LP}}{\text{LP height}} \tag{4.15}$$

8) TL shape features

Another feature, TL shape, is used to recognise CMMs. Several shape description techniques are provided in work of Lu et al. (2004). This work implements a grid method to capture the TL shape. The grid technique used was presented by Lu and Sajjanhar (1999) and the technique was reported invariant for shape scale changing, translation, rotation and mirror operation. Furthermore, this grid method is shown to be more accurate than curvature, significant edges and point techniques, and robust on slight noise (Lu and Sajjanhar, 1997). Experimentally, several grid blocks, such as 5×5 (25 features), 6×6 (36 features) and 8×8 (64 features), are applied to extract TL shape features. Empirically, the 8×8 grid provides the best classification accuracy. However, the bigger the grid is, the more computational time required.

TL shape feature extraction begins with converting the image, figure 4.22(a), to grey scale, figure 4.22(b). Then the grey colour image is changed to a binary image by applying Otsu's method for automatic threshold selection. Last, grid blocks are set to 1 with at least 15% of pixels covered by the shape while others are set to 0 (Lu and Sajjanhar, 1997). Figure 4.22(d) illustrates the grid description for the taillight shape in figure 4.22(c) binary image.

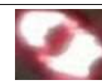


(a) (b) (c) (d)

Figure 4.22: Grid feature description of left taillight shape.

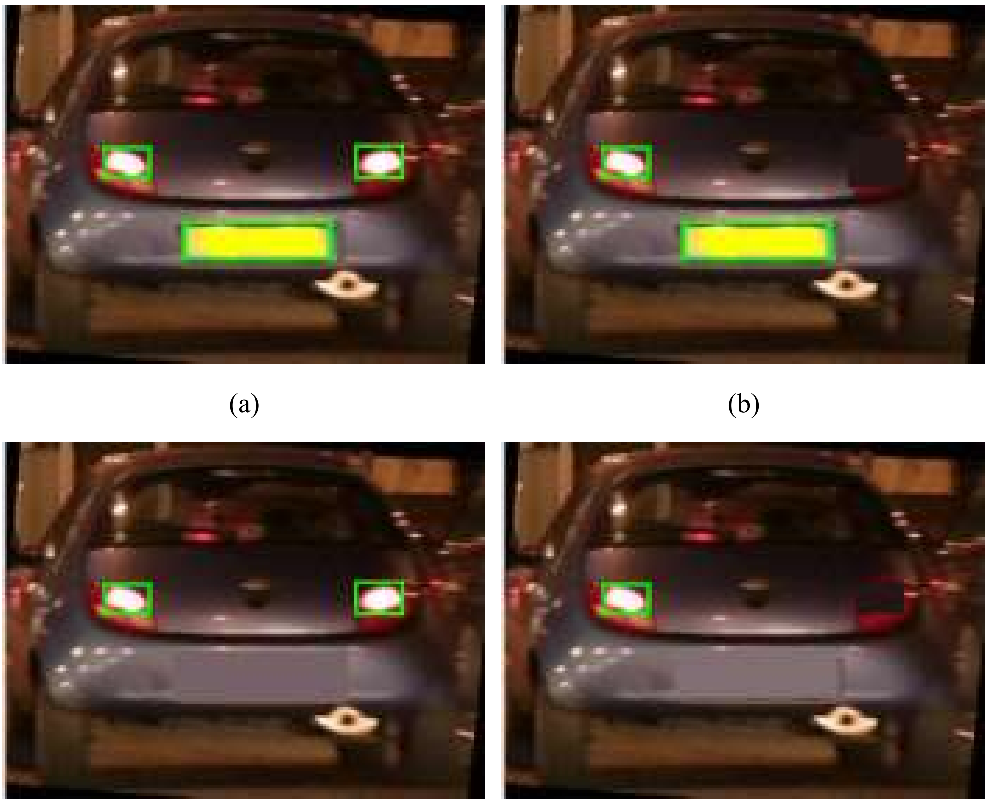
Table 4.4 shows examples of 7 geographical features and grid representation of taillight shape.

Table 4.4: Example of CMMs and features

Car model / Features	Vauxhall Astra mk4	Vauxhall Astra mk6	Vauxhall Corsa D
Image			
AR_TL	3.1	2.8	1.2
Angle-TL-LP	181.3°	147.2°	150.2°
AR_TL-LP-W	0.3	0.7	0.4
AR_TL-LP-H	0.6	0.9	1.2
AR_Dist-TL-LP-W	2.7	2.7	2.6
AR_Dist-TL-TL-W	6.1	3.6	7.2
AR_Dist-TL-LP-H	0.4	4.2	3.6
Left taillight image			
8×8 grid for left taillight	01111000 11111111 11111111 11111111 11111111 11111111 11111111 01111100	11101110 11111111 11111111 11111111 11111110 11100110 11100110 01100110	11111000 11111000 11001110 11001110 01100111 01111111 00111110 00011100

4.3.4 Feature sets

In real video images, TL and LP detection can be affected by many factors, for example, a reflection on LP, or TL and LP are obscured by other objects in the scene. Thus not all features can always be detected. Therefore, to make the method robust enough to deal with missing features, different training sets containing different features affected by different factors are studied. To do this, features are divided into four different cases or sets depending on TL and LP detection: 1) All features detection, 2) One TL and LP detection, 3) Both TLs detection, and 4) One TL detection, as shown in figure 4.23.



(a) (b)

(c) (d)

Figure 4.23: Images of incomplete feature detection sets.

1) First set (All features detected)

The first set represents the case when all features are detected, as shown in figure 4.23(a). In this case, two taillights and a licence plate are found and the entire 140 features (12 geographical features shown in table 4.3 and 128 taillight grid features) can be determined. This type of set should provide the best classification accuracy.

2) Second set (One TL and LP features detected)

In the second set, apart from the LP, only one TL is detected. The features found therefore are 5 geographical features and 64 taillight shape features. Figure 4.23(b) illustrates an image of TL and LP detection. Table 4.5 shows features of this case and the features with difference of TL side detected.

Table 4.5: Features of TL and LP detected set

No.	Left TL detected	Right TL detected
1.	Aspect ratio of left-TL	Aspect ratio of right-TL
2.	Aspect ratio of left-TL width and LP width	Aspect ratio of right-TL width and LP width
3.	Aspect ratio of left-TL height and LP height	Aspect ratio of right-TL height and LP height
4.	Angle of left-TL and LP	Angle of right-TL and LP
5.	Aspect ratio of distance left-TL to LP and LP height	Aspect ratio of distance right-TL to LP and LP height

3) Third set (Both TLs features detected)

In this case, only TLs are detected, as shown in figure 4.23(c). The features are reduced to 3 geographical features (aspect ratio of TLs and aspect ratio of distance between TLs and average of TL width) and 128 TL shape features.

4) Fourth set (One TL features detected)

In the last set, only one TL is detected. It has a TL aspect ratio value and TL shape features totalling 65 features. Figure 4.23(d) shows an image of the case where only one TL is detected.

4.3.4 Feature selection

A vehicle may have a certain group of prominent features derived from TLs and LP that make it clearly distinguishable from others. Therefore, to improve classification accuracy, a feature selection method is applied to find the best (optimized) feature subset for each car model. Not only can feature selection enhance the predictor performance, but also it can reduce computation time and enable us to understand data in machine learning (Chandrashekar and Sahin, 2014). Many feature subset selection techniques are available, such as principle component analysis (PCA), particle swarm optimization (PSO) and genetic algorithm (GA). In this work, GA is used to select the best feature subset for each car model. The GA technique, the heuristic search, is likely to offer the optimum or near optimum results that are acceptable for time consumed, or use less computation time than an exhaustive search. The GA method randomly selects some features from all features to a feature subset and then the subset is evaluated by a defined fitness function to obtain the best classification accuracy. The best feature subset is obtained after the highest accuracy has been reached. A binary GA has been used in this work to select features which seem to be more suitable than integers and floating point representation. The corresponding feature is selected if a bit string of the chromosome is a 1. The corresponding feature is not selected if its value is 0.

The basic technique of GA is designed to mimic the process in natural evolution strategies of species for survival, which follows the Charles Darwin’s principle of “survival of the fittest”. GA simulates this principle mechanism by targeting at optimal solutions in complex search space. The new populations of each generation are iteratively created by GA though genetic operations such as selection, crossover, and mutation. Two parents with high relative fitness in the initial generation are chosen in the selection process. Crossover is performed by randomly exchanging parts of selected chromosomes and mutation presents rare changing of chromosomes. Each population can be called chromosomes that are usually encoded by binary, integer, or real number types. The length of a chromosome is equal to the dimension of features. For the binary chromosome employed in this work, each binary value in a chromosome represents one corresponding to the same indexed feature in the feature set. Features are selected if the chromosome value is '1'. Otherwise, the features are not selected, if it is '0'. For example, if a generated chromosome equals {1 0 1 0 1 0 1 1}, which is 8-bit length, the feature subset consists of features {f1, f3, f5, f7, f8}.

A fitness function of GA is the objective function of the optimization problem. In this case, a fitness function is defined to increase the classification accuracy by finding a feature subset that generates less classification error. In this work, the fitness function is defined as equation 4.16.

$$\text{Class\_label}_{test,c} = \text{Predict}\,(\text{model}_{train,c}\,,\ \text{data}_{test,c})$$
$$\text{Fitness}(c^*) = \min_{i \in P} Err\,(\text{class\_label}_{train,c} \neq \text{class\_label}_{test,c}) \qquad (4.16)$$

where c is a chromosome and c^* is the optimum chromosome by GA operations. P is the entire population. $\text{Data}_{test,c}$ and $\text{model}_{train,c}$ are the test and trained model of the feature subset indexing by chromosome c. $\text{Class\_label}_{test,c}$ and $\text{class\_label}_{train,c}$ are the prediction label of the test and trained data, respectively. *Err* is the error rate of the selected subset testing.

Figure 4.24 shows a system overview of the implemented genetic algorithm to find the optimum feature subset. The algorithm starts with the GA creating the first generation, which includes a number of the entire population. Each unit of the population can be called an individual or chromosome. A chromosome is represented in bit-string '1' and '0' and maps to features set. As described earlier, features are selected when the chromosome value is 1. Then selected features are trained and then sent to the fitness function evaluation process. If the termination condition is reached, the optimized feature subset is obtained. The optimum subset will be used for a specific CMM, where these features show high confidence or prediction accuracy. On the other hand, if the termination condition is not satisfied, it will build on this population for the next generation.

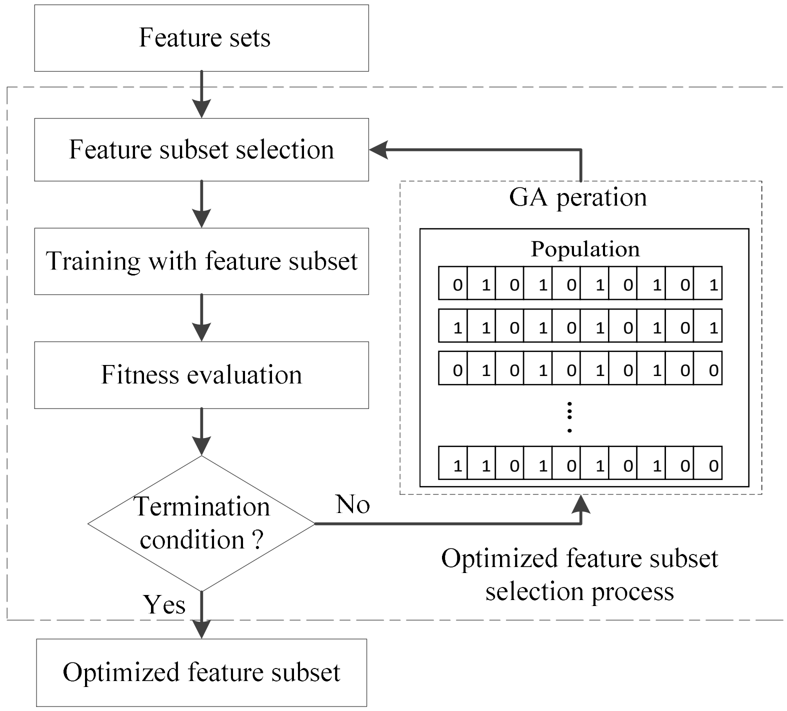


Figure 4.24: Optimized feature selection base on GA algorithm.

4.4 Classification

The objective of this process is to predict a subject car model to the predefined classes, target car model and other class. The process contains two processes, training and testing processes. In the training phrase, samples of the CMM of interest and other model images are learned and trained by classifier. After that, a trained model is obtained that can then be used to classify test data in the classification process.

As mentioned earlier, binary class classification is employed in this research to recognise target or CMM of interest in images. Three classifiers, SVM, DT, and kNN, are used together to predict test data. Majority vote is used to verify the final decision of classification. Figure 4.25 shows the proposed classification method.

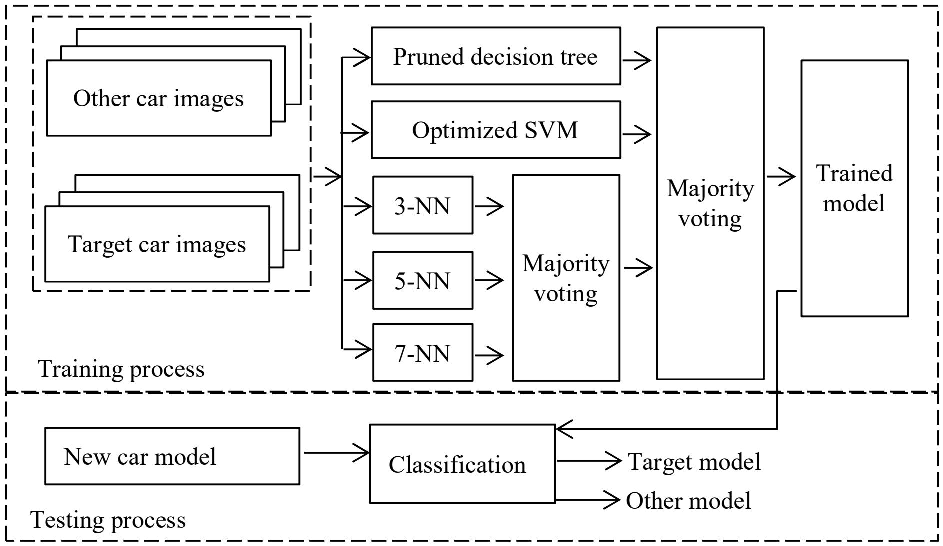


Figure 4.25: Proposed classification methodology.

From the study of Amancio et al. (2014), the classification accuracy of the SVM technique can be improved by using appropriate parameters. Therefore, this research uses radial basis function (RBF) kernel and optimized parameters are selected for the SVM. For RBF, the model parameters consist of Gaussian width, σ, and the regularization parameter, C. The variation of any of them affects the classification performance (Li et al., 2008). As reported in Valentini and Dietteich (2004), the classification performance of RBF kernel largely depends on the σ value more than C. Therefore, the research is designed to tune only the Gaussian sigma value in order to find the optimized leaning of SVM. Figure 4.26 illustrates the algorithm to find the best parameter for RBF-SVM.

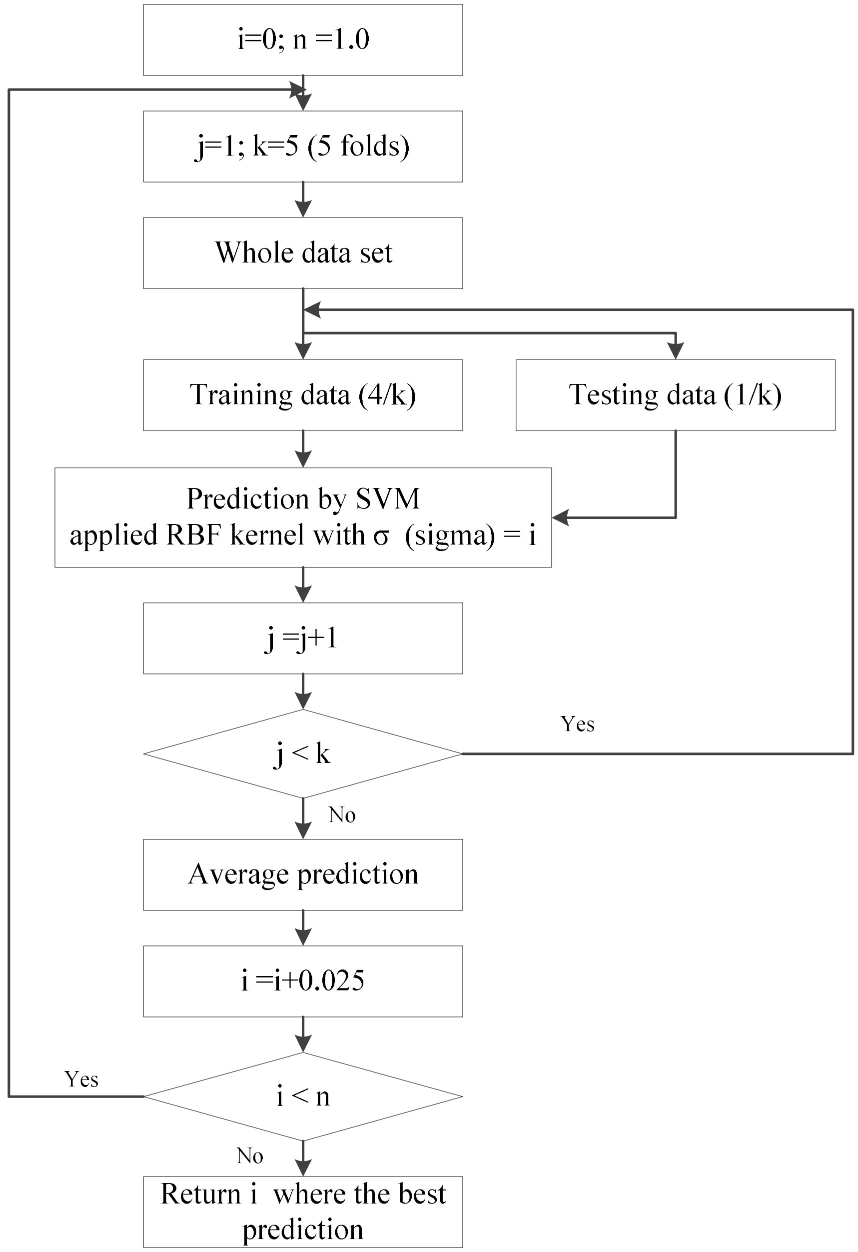


Figure 4.26: Algorithm to find optimum parameter of SVM.

The technique tests various sigma values between 0 and 1 to obtain the highest classification rate and five-fold cross-validation is used to evaluate each sigma value testing. To classify the test data, SVM score function is applied and calculates X_{test} features with all feature points m in the feature space. The highest score is considered to be the prediction class. SVM score function can be calculated as defined in equation 4.17 where c are the predesigned classes.

$$\text{SVM}_{pred} = \max_{c\,\in\,-1,+1} \sum_{i=1}^{m} \alpha_i y^c K\left(\text{X}^{\text{i}}, X_{test}\right) + b \tag{4.17}$$

A decision tree classifier predicts instances by sorting them based on feature values. Each node in a decision tree represents a feature in an instance to be classified, and each branch represents a value that node can assume. Instances are classified starting at the root node and sorted based on their feature values (Kotsiantis, 2007).

The aim of pruning a decision tree is to prevent the risk of over-fitting and poorly generalizing to new sample. When the tree is over-fitting it might be lead to error in classification. Thus, decision tree pruning is used in this research. The maximum probability of testing features with trained class features is applied to classify test data as equation 4.18.

$$\text{DT}_{pred} = \max_{c\,\in\,-1,+1} p(X_c|t) \tag{4.18}$$

where $p(X_c|t)$ is feature probability value to predefined class c at node t.

K-nearest neighbours (kNNs) is the instance base learning which classifies the test data by comparing to the k nearest training data based on a distance function (Kotsiantis, 2007). In this work, a Euclidian function is used to measure distance. Majority vote of three, five and seven nearest neighbours is used to crop the variance data and to emphasise the final prediction. Predicting the class of the test data is defined as in equation 4.19, where c are the predesigned classes and k is the number of neighbours.

$$\text{NN}_{pred} = \min_{c\,\in\,-1,+1} dist(\sqrt{(\text{X}_c - \text{X}_{test})^2}) \tag{4.19}$$

$$\text{kNN}_{pred} = \frac{1}{k}\,\text{kNN}_{pred}$$

where X_c and X_{test} mean predefined classes and test features. Minimum distance between test data and predefined classes data is used to verify prediction of this method. Majority vote is employed to predict the final decision of the three classifiers. Prediction of those classifiers is calculated to have final vote as equations 4.21 and 4.22.

$$\Phi = (\frac{1}{3}(SVM_{pred} + kNN_{pred} + DT_{pred})) \tag{4.21}$$

$$\text{Final prediction} = \begin{cases} -1, \Phi < 0.5 \\ +1, \Phi \geq 0.5 \end{cases} \tag{4.22}$$

where Φ is a numerical value which is calculated from the three classifier predictions.

4.5 Training over-fit handling

Basically, classification process consists of two processes: training and classification. In training process, classifier techniques try to fit model or minimize classification error to a set of training data in order to have good model and high classification accuracy. Therefore, it leads to over-fitting or overtraining model.

Over-fitting occurs when the trained model provides good or perfect result in some dataset but it does not generalize the good classifying to new or unseen data. Generally, over-fitting will emerge when a model is excessively complex, such as having too many parameters relative to number of observations and the incompatible of model structure with data shape (Domingos, 2012).

Many techniques have been presented in order to avoid over-fitting for example, cross validation, regularization, early stopping, pruning, Bayesian prior and feature selection (Domingos, 2012).

The proposed method uses various techniques such as feature selection, cross validation, pruning technique and as much as a few parameters used strategy. First, feature selection is implemented to select distinguishable features of each car model and in order to reduce a number of features. With a smaller number of features than observations (data training), it could be avoid the over-fitting. Next, cross validation is used in feature selection and training steps to reduce the bias and variance of data and then it may reduce the opportunity of over-fitting. Third, the research implements decision tree with pruning method and k-NN classifier which has only one (k) parameter to classify car model that could be avoid the over-fitting(Domingos, 2012).

4.6 Class imbalance problem handling

In the proposed classification method, binary classification is applied to predict between target car model and other model. This strategy raises the class imbalance problem where the target model is greatly underrepresented compared to examples of the other model class. Several techniques have been used to solve the problem of class imbalance (Galar et al., 2012). This research uses a data sampling technique, synthetic minority oversampling technique (SMOTE), implemented at data level and there is no modification to the proposed classification method. The sampling technique adds new samples to the minority (target) class by randomly choosing from k nearest neighbours (Chawla et al., 2002). After applying the technique, the target model will increase the balance of class distribution. The target class is designed to oversample to 10% of other class samples. Then the dataset can be classified by the designed classification process.

CHAPTER 5

EXPERIMENT RESULTS

This chapter provides the research project evaluation. The performance of the proposed technique is measured its accuracy. The experiments were separately tested on each feature subset, given in section 4.3.4. Several classifiers were also tested on the same dataset in order to compare against the proposed technique. In addition, system implementation details, dataset and analysis of experimental results are explored.

5.1 System implementation

This covers system implementation including machine specification, operating system, software, application file format and programming language. Moreover, data collection and image pre-processing are introduced.

5.1.1 Platform

The proposed technique is implemented on a computer with 2.1 GHz Pentium Dual-core CPU and 4GB RAM. The operating system installed on the computer is Windows 7 Enterprise 32-bit.

5.1.2 Software and Programming language

Image processing software AVS video convertor was used to extract image frames from the video stream file. In addition, the programming language MATLAB version R2013a was used to implement the proposed method. In the image pre-processing step, image processing toolbox including image manipulating functions – histogram equalization, image transformation, morphological operations and edge detection – was employed. A statistical toolbox was utilized in classification process. The toolbox consists of classifiers, training functions, prediction functions and classification performance evaluation functions. Furthermore, CSV file format was used to store all features of the dataset, which can be easily imported into MATLAB.

5.2 Data set

The research data set, the images, were collected in a city area at night by video digital camera, as shown in figure 5.1. The video data were taken of passing cars in rear view with the distance from camera within 50 metres. After that, images were extracted from the obtained video data and were manually labelled with their makes and models. Figure 5.2 shows examples of captured car images.

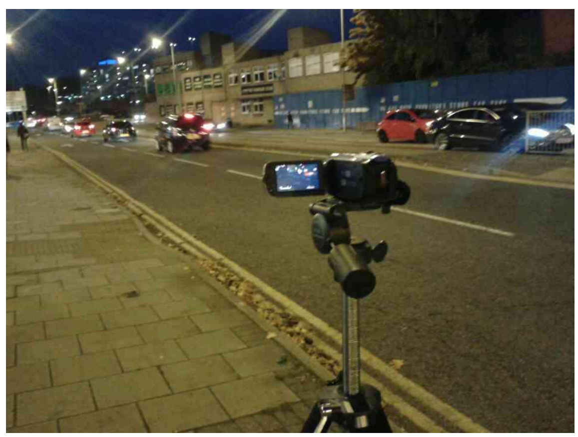


Figure 5.1: Camera view setup.

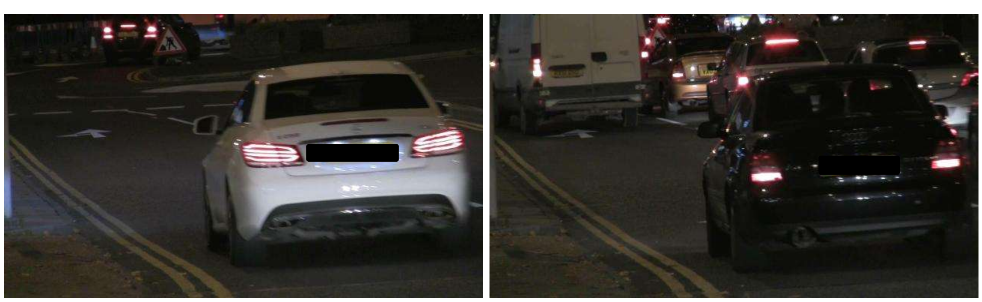


Figure 5.2: Samples of captured car rear view image.

The data set contains 421 car models with a total of 766 images. This data set consists of two types of car models: target car model and other model. There are 100 target car models used to train and then classify against other models. Each target car model contains at least 4 images (samples) and there is one image per other-car model. Figure 5.3 and figure 5.4 show sample images of target car models and other-car models, respectively.

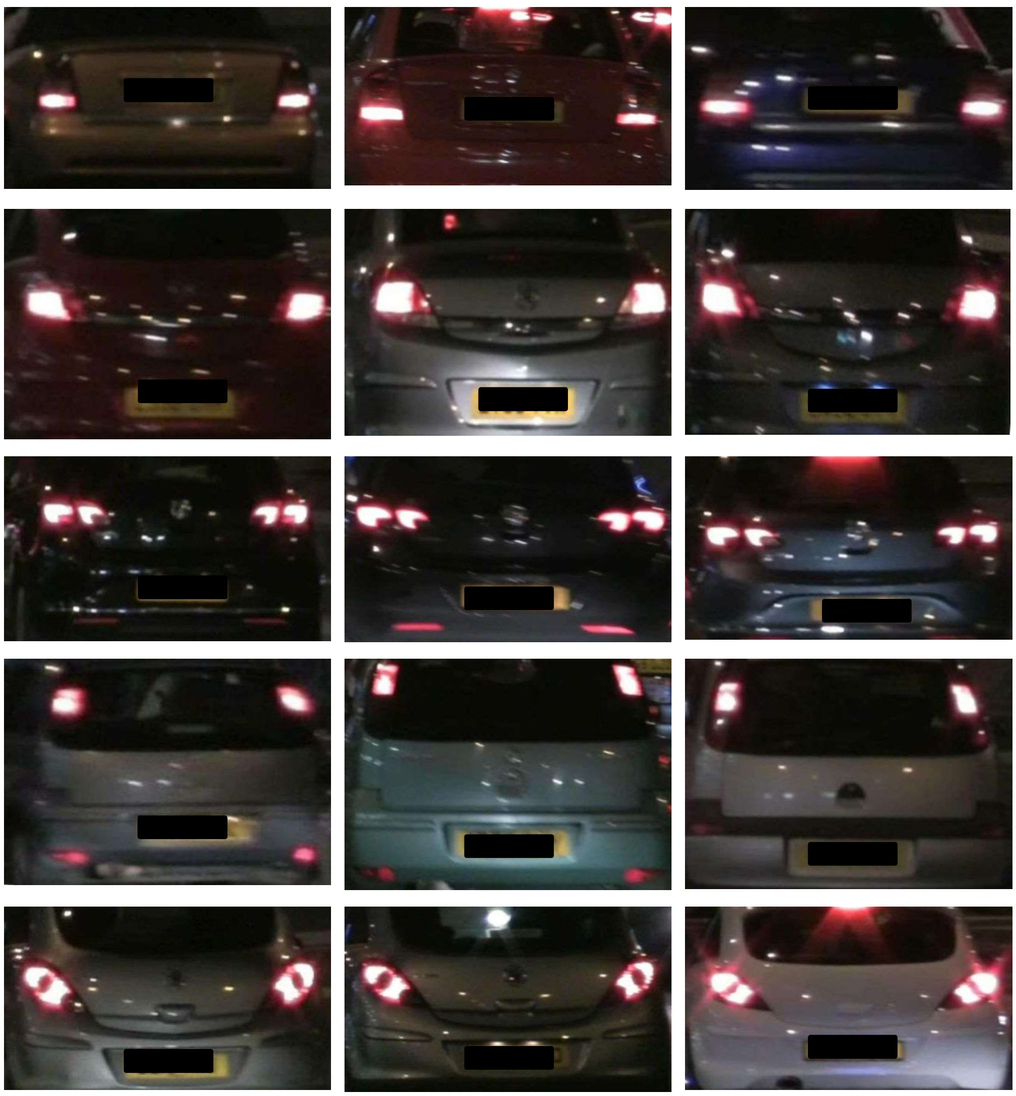


Figure 5.3: Example target car model images.

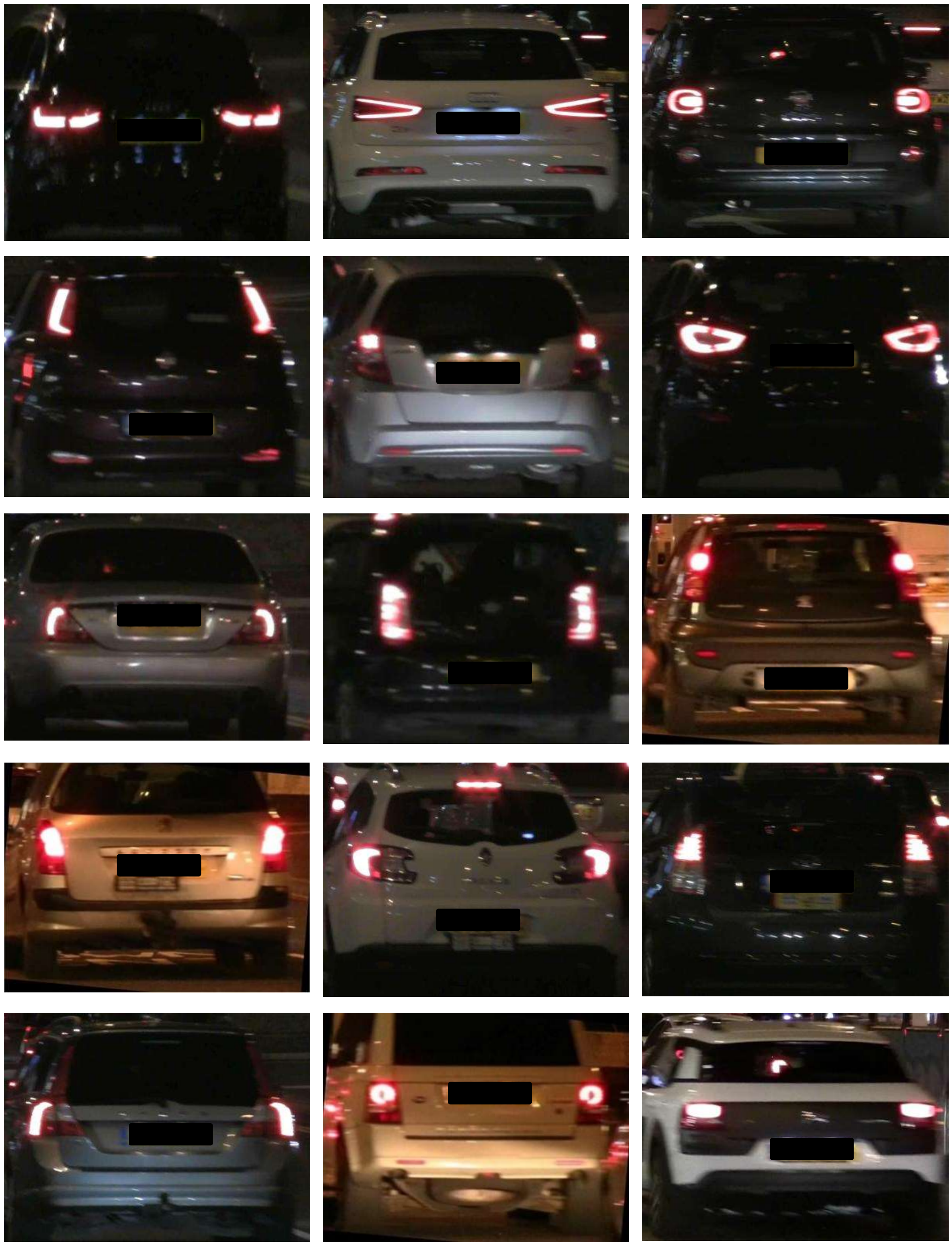


Figure 5.4: Example other-car model images.

The car model can be organised into a hierarchy structure with three layers, namely, car make, car model and generation from top to bottom, as shown in figure 5.5. In figure 5.5, for example, the Toyota Company produced the Yaris car model in three generations, and each generation contains at least one model. Car models were assigned by model code, for instance, XP150.

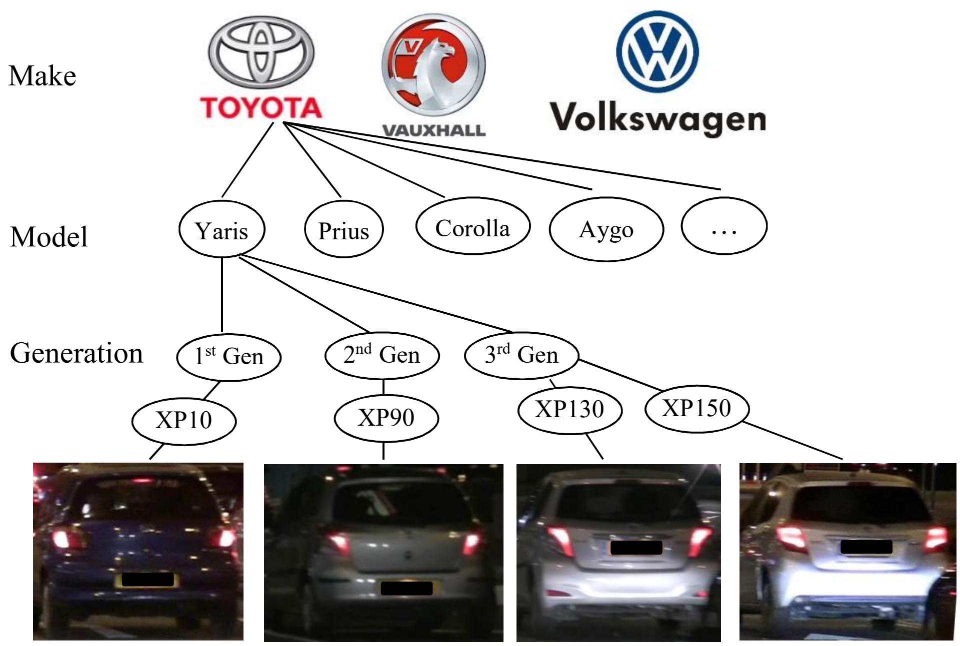


Figure 5.5: Car make and model structure hierarchy.

As mentioned in the previous chapter, images were resized to associate with designed thresholds and reduce implementation times. All image frames were resized from 1920×1080 to 640×480 pixels. Next, videos were experimentally taken on the left side of a road. Then images were rotated in the clockwise direction by 5° with the fixed angle of camera. Last, car features of all models were manually extracted and then used in the experiment process.

This research has been followed with University of Bedfordshire ethical guideline about using real data (images). Therefore, all images used have been covered or blanked on licence plate in order to no specific car can be identified in this research.

5.3 Experiment setup

The objective of experiments is to evaluate the performance of the proposed technique. To achieve this, the experiments need to be carefully conducted. An experimental dataset was created and discussed in the previous section and separated into four sets depending on taillight and licence plate detection as follows.

1) First set (All features detected)
2) Second set (One TL and LP features detected)
3) Third set (Both TLs features detected)
4) Fourth set (One TL features detected)

The experiments were separately conducted on each feature set. Various classifiers, for example, linear SVM, kernel SVM, decision tree, nearest neighbour, were evaluated on the dataset in order to compare with the proposed method. Classification accuracy performances were evaluated by cross-validation on the obtained dataset. The cross-validation technique is randomly separated into training set and testing set. The research uses ten-fold cross-validation and algorithm is shown in figure 5.6.

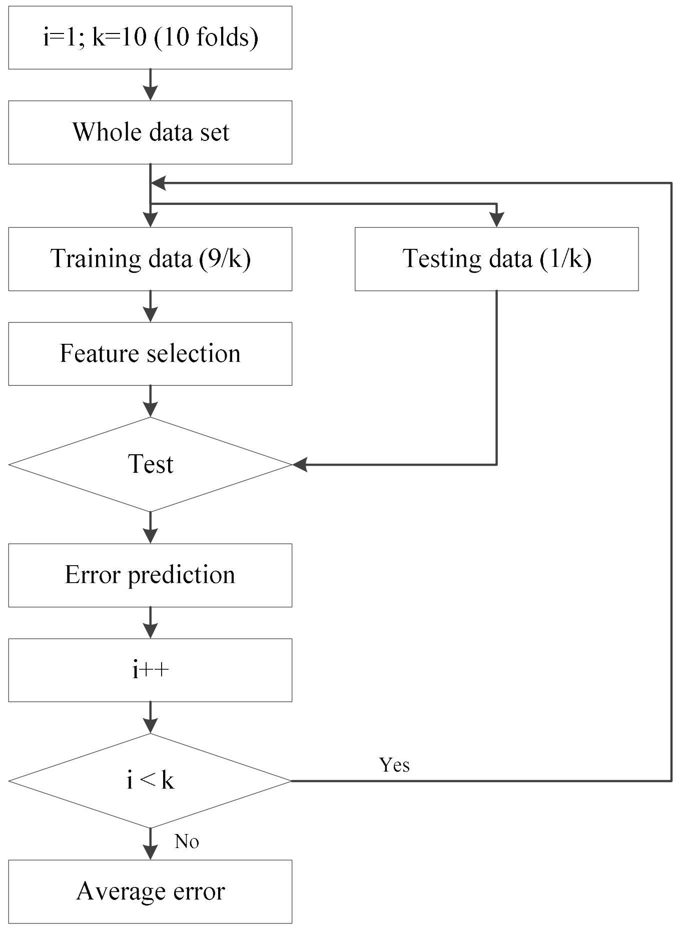


Figure 5.6: Ten-fold cross-validation algorithm for accuracy evaluation.

The accuracy evaluation of cross-validation is calculated from the average value of all experiments as indicated in equation 5.1.

$$\text{Classification accuracy} = 100 - \frac{\sum_{1}^{k} Error}{k} \qquad (5.1)$$

where *k* is the number of folds used to validate the dataset.

5.4 Experimental results

This section provides all experiment results including feature detection processes (LP detection and LP detection) and CMMR classification accuracy. First, the LP and TL detection accuracies, as shown in table 5.1, were reported 96.52% and 95.37 %, respectively. Last, the classification accuracies of 100 target models of the proposed method are shown in table 5.2. Each target model was tested against 420 other models by using ten-fold cross-validation; four feature sets were evaluated separately.

Table 5.1: feature detection performances.

Feature detection	Accuracy (%)
Licence plate detection (Mendes et al., 2011)	96.52
Taillight detection (Boonsim et al., 2014)	95.37

Table 5.2: Classification accuracy (%) results.

No	Car models	False positive	False Negative	Precision	Recall	Accuracy
1	VAUXHALL ASTRA MK4	4.1	2.1	59.1	74.3	92.4
2	VAUXHALL ASTRA MK5	4.6	1.7	61.2	80.8	92.0
3	VAUXHALL ASTRA MK6	4.4	1.8	62.0	79.5	92.6
4	VAUXHALL CORSA C	4.7	1.5	58.2	81.4	93.2
5	VAUXHALL CORSA D	5.0	0.1	71.1	99.1	93.6
6	FORD FIETA MK6	4.5	0.2	67.7	97.7	93.8
7	FORD FOCUS MK2	5.0	0.8	70.3	94.0	93.4
8	NISSAN MICRA K12	4.6	1.7	63.4	82.6	91.4
9	NISSAN QASHQAI J10	3.5	0.4	74.8	95.8	93.4
10	SKODA OCTAVIA 1U	5.2	1.7	57.4	80.5	93.4
11	TOYOTA AVENSIS T250	3.4	0.0	76.6	100.0	93.2
12	LONDON TAXI TX4	5.4	1.1	59.0	87.3	95.0
13	VAUXHALL ADAM	3.1	0.3	77.6	97.0	95.2
14	VOLKSWAGEN PASSAT B6	4.5	0.8	68.0	92.4	92.6
15	VAUXHALL ZAFIRA	2.9	0.3	79.2	97.1	93.2
16	VAUXHALL VECTRA	2.7	0.4	80.5	96.1	93.6

No	Car models	False positive	False Negative	Precision	Recall	Accuracy
17	VAUXHALL ASTRA GTC	2.6	0.1	81.7	99.0	94.2
18	AUDI A3 8V	2.6	0.1	81.9	99.0	94.8
19	AUDI A4 B7	2.5	0.0	82.8	100.0	94.0
20	AUDI A1	5.4	0.6	60.0	93.5	95.4
21	AUDI A3 8P	4.5	0.6	67.5	94.3	95.6
22	AUDI Q7	3.3	0.1	77.2	99.0	95.0
23	AUDI S5	4.5	1.0	66.4	89.8	92.4
24	BMW 1S E87	4.2	0.8	69.4	92.3	95.2
25	BMW 3S E92	3.8	1.0	70.9	90.2	93.2
26	BMW 5S F10	3.9	0.8	71.1	92.5	93.8
27	CITROEN C3 1ST GEN	4.7	0.8	65.3	91.9	94.4
28	AUDI A4 B6	3.7	0.4	73.4	95.8	94.2
29	CITROEN XSARA PICASSO	3.8	0.3	72.8	96.8	93.8
30	CITROEN C3 PICASSO	3.5	0.2	75.4	97.9	95.6
31	CITROEN C5 DC	4.5	1.0	66.7	89.9	94.8
32	VAUXHALL CORSA B	5.5	0.4	60.5	94.9	95.4
33	FIAT GRADE PUNTO	5.3	1.3	59.1	85.0	95.2
34	FIAT 500	5.1	0.8	62.2	91.4	95.0
35	FORD C-MAX MK1	4.6	1.2	63.4	86.6	93.8
36	FORD FIETA ST	4.7	1.9	61.1	79.5	94.4
37	FORD FIESTA MK5	3.9	1.5	67.0	84.5	93.6
38	FORD FOCUS MK1	4.8	1.7	62.3	82.6	93.8
39	FORD FOCUS ST	4.5	1.6	64.3	83.7	93.8
40	FORD KA	4.5	1.5	64.9	85.1	92.8
41	FORD MONDEO MK3	4.4	0.2	68.8	97.7	93.4
42	FORD TRANSIT CONNECT	4.4	0.7	68.0	93.3	91.8
43	HONDA CRV RD4	4.4	0.4	68.8	95.6	93.2

No	Car models	False positive	False Negative	Precision	Recall	Accuracy
44	HONDA CRV RM1	4.2	1.1	68.6	89.0	93.0
45	HONDA JAZZ 1ST GEN	3.9	0.7	71.1	93.5	94.6
46	HONDA CIVIC MK8	3.9	0.4	71.8	95.7	92.0
47	LAND ROVER RANGE ROVER	3.8	0.1	73.2	98.9	91.8
48	MERCEDES A140	3.9	0.3	72.4	96.8	91.4
49	MERCEDES C-CLASS W202	3.7	0.2	74.0	97.9	92.0
50	MERCEDES C-CLASS W203	3.5	0.1	75.6	99.0	92.8
51	MERCEDES C-CLASS W204	4.8	1.8	59.0	79.5	93.4
52	MERCEDES E-CLASS COUPE	5.2	2.5	55.3	72.2	92.2
53	MINI COUNTRYMAN	5.2	0.9	61.0	90.0	97.2
54	NISSAN JUKE	5.2	1.0	61.0	88.9	94.6
55	NISSSAN MICRA TEMPEST	4.9	1.1	62.1	87.8	96.8
56	PEUGEOT 206	4.5	1.7	63.0	81.9	96.6
57	PEUGEOT 206 GTI	4.3	1.2	65.8	86.9	96.4
58	PEUGEOT 207 GT	4.6	1.6	63.4	83.5	95.4
59	RENAULT SCENIC CONQUEST	4.6	1.9	62.7	80.2	95.4
60	RENAULT CLIO2	4.4	1.2	66.4	87.5	95.6
61	RENAULT CLIO4	5.1	1.1	60.2	87.2	95.4
62	RENAULT MEGANE COUPE CABRIO	5.3	1.1	59.5	87.3	97.2
63	RENAULT MEGANE MK2	4.9	0.9	62.1	90.0	97.2
64	SEAT IBIZA MK2	5.1	0.7	62.5	92.6	96.8
65	SEAT IBIZA MK3	4.8	1.5	61.6	84.1	96.8
66	SEAT IBIZA MK4	4.9	2.9	56.4	68.7	90.8
67	SEAT IBIZA MK4 ST	4.6	0.3	66.4	96.4	89.8

No	Car models	False positive	False Negative	Precision	Recall	Accuracy
68	SKODA OCTAVIA COMBI	4.3	1.3	65.8	85.9	90.2
69	TOYOTA ECHO 1^{ST} GEN	4.4	1.1	66.1	88.4	91.6
70	TOYOTA PRIUS 3^{TH} GEN XP30	4.7	0.2	66.9	97.7	91.0
71	TOYOTA YARIS XP90	4.6	1.5	64.7	85.2	91.8
72	TOYOTA YARIS XP130	5.5	1.7	56.6	81.0	92.0
73	VAUXHALL INSIGNA	4.2	0.9	68.9	91.1	90.4
74	VAUXHALL MOKKA	4.9	2.4	57.7	74.1	91.6
75	VAUXAHLL TIGRA	3.9	0.9	70.6	91.3	92.2
76	VAUXHALL CASCADA	4.7	1.0	63.8	89.2	94.2
77	VOLKSWAGEN GOLF MK4	3.8	0.7	71.7	93.5	94.0
78	VOLKSWAGEN GOLF MK5	4.2	1.5	66.1	84.7	94.0
79	VOLKSWAGEN GOLF MK6	3.7	0.6	73.4	94.8	93.2
80	VOLKSWAGEN NEW BEETLE	4.6	0.3	67.2	96.6	93.0
81	VOLKSWAGEN PASSAT B5	3.4	0.7	75.4	93.9	95.6
82	VOLKSWAGEN PASSAT B7	4.3	1.2	67.2	87.6	91.4
83	VOLKSWAGEN PASSAT CC	3.1	0.0	78.1	100.0	93.1
84	VOLKSWAGEN POLO GTI MK4	4.0	0.6	70.5	94.5	93.0
85	VOLKSWAGEN POLO GTI MK6	2.9	0.6	78.9	95.1	93.4
86	VOLKSWAGEN POLO MK4	3.9	0.3	72.0	96.8	94.6
87	FORD GALAXY	3.1	0.0	78.1	100.0	94.4
88	VOLKSWAGEN TOURAN	3.7	0.2	73.8	97.9	93.6
89	VOLKSWAGEN UP	3.6	0.2	74.6	97.9	93.4

No	Car models	False positive	False Negative	Precision	Recall	Accuracy
90	VOLKSWAGEN TRANSPORT T5	3.4	0.1	76.2	99.0	93.4
91	AUDI S6	3.4	0.6	75.6	94.9	92.6
92	AUDI A3 3RD GEN	3.3	0.3	76.8	97.0	95.4
93	BMW M5 F10	3.1	0.1	78.0	99.0	95.2
94	BMW 5S E60	2.9	0.6	78.7	95.0	95.0
95	PEUGEOT 207	2.8	0.3	79.8	97.1	94.8
96	TOYOTA COROLLA 9TH GEN	2.8	0.0	80.5	100.0	94.6
97	FIAT PUNTO	2.7	0.1	81.1	99.0	93.6
98	TOYOTA VENZA V6	2.5	0.2	82.4	98.1	94.2
99	ALFA ROMEO MITO QV	2.5	0.0	82.8	100.0	93.8
100	AUDI A2	2.4	0.0	83.6	100.0	93.6
	Average (%)	4.1	0.8	69.0	91.3	93.78

In table 5.2, the average classification accuracy on 100 target car models is 93.78 % and the average false positive (false alarm) is 4.1%. In addition, the average of false negative, precision and recall are 0.8%, 69.0% and 91.3%, respectively. From the experiments using a number of car makes and models the proposed technique shows promising classification results with more than 90% accuracy. In addition, the false positive and false negative rates are less than 5 % and 1% respectively.

As discussed in the literature, there are no published works specifically dealing with the problem of CMMR at night. Also, this research evaluated variety of other classifiers with default parameters on the same data set in order to compare the results with those produced by the proposed technique. Table 5.4 shows the experimental results from each of the classifiers. It can be seen that the proposed technique performs better than the other methods. Furthermore, it is shown that particular features of some car models affect the classification accuracy. For example, the first highest classification accuracy was Mini Countryman, figure 5.7(a), which has the classification accuracy of 97.20%, and the second was Renault Megane MK2, figure 5.7(b), with the classification accuracy of 97.05 %. From the observation, those car models have very unique taillight shapes, sizes and angles between taillight and licence plate position, easier for the classifier to distinguish them.

(a) (b)

Figure 5.7: Target car model images of the highest classification accuracy.

Table 5.3: Classification accuracy (%) results of each set.

No	Car models	1^{st} set	2^{nd} set	3^{rd} set	4^{st} set	Average by model
1	VAUXHALL ASTRA MK4	92.4	93.0	90.6	91.0	91.8
2	VAUXHALL ASTRA MK5	92.0	93.2	92.0	91.8	92.3
3	VAUXHALL ASTRA MK6	92.6	93.4	93.2	92.8	93.0
4	VAUXHALL CORSA C	93.2	91.6	92.4	91.8	92.3
5	VAUXHALL CORSA D	93.6	93.2	93.2	93.2	93.3
6	FORD FIETA MK6	93.8	93.6	93.2	93.4	93.5
7	FORD FOCUS MK2	93.4	93.2	93.4	93.2	93.3

No	Car models	1st set	2nd set	3rd set	4st set	Average by model
8	NISSAN MICRA K12	91.4	91.8	93.0	92.4	92.2
9	NISSAN QASHQAI J10	93.4	93.2	93.6	93.8	93.5
10	SKODA OCTAVIA 1U	93.4	93.2	93.8	92.8	93.3
11	TOYOTA AVENSIS T250	93.2	93.8	93.4	93.8	93.6
12	LONDON TAXI TX4	95.0	95.2	95.2	94.4	94.9
13	VAUXHALL ADAM	95.2	95.2	95.2	95	95.2
14	VOLKSWAGEN PASSAT B6	92.6	93.6	92.4	93.4	93.0
15	VAUXHALL ZAFIRA	93.2	93.4	93.4	92.6	93.2
16	VAUXHALL VECTRA	93.6	93.6	93.6	92.8	93.4
17	VAUXHALL ASTRA GTC	94.2	94.4	94.4	94.4	94.4
18	AUDI A3 8V	94.8	94.0	94.4	93.8	94.3
19	AUDI A4 B7	94.0	94.2	94.4	93.6	94.1
20	AUDI A1	95.4	94.8	95.8	95.8	95.5
21	AUDI A3 8P	95.6	95.4	95.0	95.2	95.3
22	AUDI Q7	95.0	94.6	94.8	95.0	94.9
23	AUDI S5	92.4	93.4	92.6	93.4	93.0
24	BMW 1S E87	95.2	95.6	94.4	94.4	94.9
25	BMW 3S E92	93.2	93.6	93.6	93.2	93.4
26	BMW 5S F10	93.8	94.6	94.4	94.2	94.3
27	CITROEN C3 1ST GEN	94.4	93.0	93.6	94.4	93.9
28	AUDI A4 B6	94.2	94.0	92.8	92.8	93.5
29	CITROEN XSARA PICASSO	93.8	93.8	92.8	93.4	93.5
30	CITROEN C3 PICASSO	95.6	95.6	95.6	95.6	95.6

No	Car models	1st set	2nd set	3rd set	4st set	Average by model
31	CITROEN C5 DC	94.8	94.6	94.8	93.8	94.5
32	VAUXHALL CORSA B	95.4	95.4	95.4	95.2	95.4
33	FIAT GRADE PUNTO	95.2	95.0	95.0	94.6	95.0
34	FIAT 500	95.0	94.8	95.0	94.8	94.9
35	FORD C-MAX MK1	93.8	95.0	84.2	94	91.8
36	FORD FIETA ST	94.4	94.2	93.8	92.6	93.8
37	FORD FIESTA MK5	93.6	94.0	94.4	94.4	94.1
38	FORD FOCUS MK1	93.8	93.4	92.8	92.4	93.1
39	FORD FOCUS ST	93.8	92.6	93.8	93.8	93.5
40	FORD KA	92.8	92.6	93.0	93.4	93.0
41	FORD MONDEO MK3	93.4	93.4	93.0	93.0	93.2
42	FORD TRANSIT CONNECT	91.8	93.2	93.0	93.0	92.8
43	HONDA CRV RD4	93.2	92.8	93.2	93.2	93.1
44	HONDA CRV RM1	93.0	93.4	94.6	94.2	93.8
45	HONDA JAZZ 1ST GEN	94.6	94.2	94.8	94.8	94.6
46	HONDA CIVIC MK8	92.0	92.0	91.4	92.2	91.9
47	LAND ROVER RANGE ROVER	91.8	91.8	91.8	92.0	91.9
48	MERCEDES A140	91.4	90.4	91.2	90.0	90.8
49	MERCEDES C-CLASS W202	92.0	91.0	92.0	92.0	91.8
50	MERCEDES C-CLASS W203	92.8	93.0	93.6	93.6	93.3
51	MERCEDES C-CLASS W204	93.4	93.2	93.6	93.6	93.5
52	MERCEDES E-CLASS Coupe	92.2	92.6	93.2	93	92.8
53	MINI COUNTRYMAN	97.2	97.2	97.2	97.2	97.2

No	Car models	1st set	2nd set	3rd set	4st set	Average by model
54	NISSAN JUKE	94.6	94.2	94.6	94.6	94.5
55	NISSSAN MICRA TEMPEST	96.8	96.8	96.8	96.8	96.8
56	PEUGEOT 206	96.6	96.2	96.6	96.4	96.5
57	PEUGEOT 206 GTI	96.4	96.4	96.4	96.2	96.4
58	PEUGEOT 207 GT	95.4	94.8	95.8	96.2	95.6
59	RENAULT SCENIC CONQUEST	95.4	96.0	95.0	95.6	95.5
60	RENAULT CLIO2	95.6	95.4	94.8	95	95.2
61	RENAULT CLIO4	95.4	95.2	95.6	95.6	95.5
62	RENAULT MEGANE COUPE CABRIO	97.2	97.0	97.0	96.6	97.0
63	RENAULT MEGANE MK2	97.2	97.0	97.0	97.0	97.1
64	SEAT IBIZA MK2	96.8	97.0	96.6	96.6	96.8
65	SEAT IBIZA MK3	96.8	96.8	96.8	96.8	96.8
66	SEAT IBIZA MK4	90.8	91.2	91.0	92.6	91.4
67	SEAT IBIZA MK4 ST	89.8	89.6	89.6	90.6	89.9
68	SKODA OCTAVIA COMBI	90.2	91.2	91.0	92.2	91.2
69	TOYOTA ECHO 1ST GEN	91.6	91.8	92.4	91.8	91.9
70	TOYOTA PRIUS 3TH GEN XP30	91.0	90.0	90.8	90.4	90.6
71	TOYOTA YARIS XP90	91.8	93.2	91.2	92.4	92.2
72	TOYOTA YARIS XP130	92.0	93.0	92.2	93.4	92.7
73	VAUXHALL INSIGNA	90.4	92.0	92.0	92.6	91.8
74	VAUXHALL MOKKA	91.6	92.2	91.2	92.4	91.9

No	Car models	1st set	2nd set	3rd set	4st set	Average by model
75	VAUXAHLL TIGRA	92.2	91.8	92.4	92.4	92.2
76	VAUXHALL CASCADA	94.2	93.6	94.0	92.0	93.5
77	VOLKSWAGEN GOLF MK4	94.0	93.8	94.0	92.6	93.6
78	VOLKSWAGEN GOLF MK5	94.0	94.0	93.4	93.8	93.8
79	VOLKSWAGEN GOLF MK6	93.2	93.2	94.0	94.0	93.6
80	VOLKSWAGEN NEW BEETLE	93.0	93.0	93.8	93.8	93.4
81	VOLKSWAGEN PASSAT B5	95.6	95.6	94.8	95.4	95.4
82	VOLKSWAGEN PASSAT B7	91.4	92.6	92.4	93.4	92.5
83	VOLKSWAGEN PASSAT CC	93.1	93.0	93.0	93.2	93.1
84	VOLKSWAGEN POLO GTI MK4	93.0	92.8	92.8	93.2	93.0
85	VOLKSWAGEN POLO GTI MK6	93.4	94.2	94.4	94.8	94.2
86	VOLKSWAGEN POLO MK4	94.6	93.8	94.6	94.2	94.3
87	FORD GALAXY	94.4	94.4	94.4	94.4	94.4
88	VOLKSWAGEN TOURAN	93.6	94.2	93	92.8	93.4
89	VOLKSWAGEN UP	93.4	93.8	92.8	93.8	93.5
90	VOLKSWAGEN TRANSPORT T5	93.4	93.8	93.6	93.4	93.6
91	AUDI S6	92.6	93.4	92.6	92.8	92.9
92	AUDI A3 3RD GEN	95.4	95.2	95.2	95.4	95.3
93	BMW M5 F10	95.2	95.0	94.8	94.8	94.5
94	BMW 5S E60	95.0	95.0	94.8	94.6	94.4

No	Car models	1^{st} set	2^{nd} set	3^{rd} set	4^{st} set	Average by model
95	PEUGEOT 207	94.8	94.2	94.8	94.8	94.2
96	TOYOTA COROLLA 9^{TH} GEN	94.6	94.0	93.2	94.2	94.0
97	FIAT PUNTO	93.6	92.4	93.2	94.2	94.2
98	TOYOTA VENZA V6	94.2	93.8	93.0	94.2	94.3
99	ALFA ROMEO MITO QV	93.8	94.0	93.6	94.0	93.9
100	AUDI A2	93.6	93.6	93.6	93.8	93.7
	Average by feature set (%)	93.77	93.97	93.56	93.83	93.78

From table 5.3, the classification accuracy on the second set outperforms other feature sets. The average accuracy is accounted at 93.97% following by the fourth, first and third feature sets, respectively. However, the experiments are tested on 100 CMMs. It is possible that prediction accuracy could be changed by increasing the number of CMMs in dataset. In section 4.3.4, the number of features in each feature subset was discussed. The first set has 140 features, which is the largest feature number of all feature subsets. Although the first set has the highest number of features, the prediction rate of the set was not reported with the highest classification accuracy. From observation, the classification accuracy depends on the discriminant features used rather than a number of features. Moreover, using many features may have redundant features that lead to decrease accuracy and increase time consumed.

From the experiments, it can be noted from table 5.4 that the proposed method reported the highest average classification accuracy at about 93.78%, which outperforms other methods including linear SVM, radial basis function SVM (RBFSVM), decision tree nearest neighbour and no applied feature selection. Although the proposed technique illustrated high prediction accuracy, computational times to seek optimum features were very large.

Table 5.4: Comparison with other classification methods.

Classification methods	1st set	2nd set	3rd set	4st set	Average accuracy (%)
Linear SVM	88.76	88.71	88.34	88.21	88.50
RBF SVM (sigma = 0.5)	86.68	87.88	86.82	87.81	87.30
Decision tree	91.37	91.46	91.24	91.31	91.34
Nearest neighbour	92.17	92.26	91.86	91.83	92.03
No applied feature selection	93.22	93.76	93.19	93.58	93.43
Proposed method	93.77	93.97	93.56	93.83	93.78

In the training process, the no applied feature selection method consumed about a minute to train classifiers. On the other hand, GA was computationally expensive. It was about 70 times that of no applied features selection. Figure 5.8 shows CMM training time of the two methods.

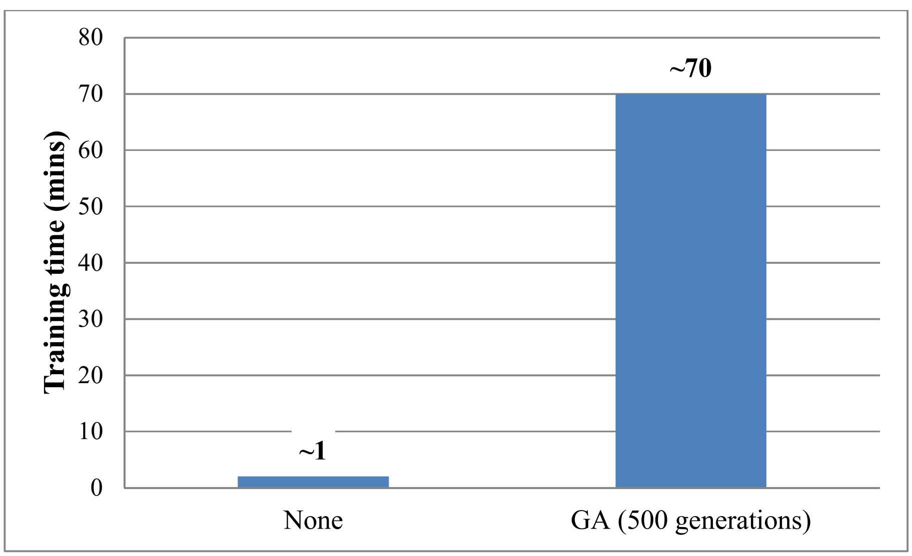


Figure 5.8: Comparison of training time of GA method with no applied feature selection.

Even though GA training was reported as highly time-consuming, the training work is basically implemented in an offline process. Thus, the large computation time can be accepted. In addition, the system was implemented using MATLAB. If the algorithm employed other technologies, the computation times may be decreased.

CHAPTER 6
CONCLUSION

This chapter presents the conclusions of the research and future works. The aim of this research is to present a car make and model recognition (CMMR) technique to work under limited lighting at night. The technique should not only recognise car make and model but also classification performance should be satisfied.

The majority of previous CMMR works presented are for daytime where visual appearances are clearly obtained. Several techniques, for example, edge-based feature and texture-based feature, are proposed in daytime and classification accuracy rates of these techniques were reported at more than 90%. Unlike daytime, at night, there are few appearances, head-lights, tail-lights, and licence plate, which can be used to recognition car models. In addition, capturing images at night poses light reflection problems. Reflections might occur from many light sources at night, such as street-lamps, headlights, taillights and brake-lights of other cars which will interfere with car appearances. Therefore, CMMR techniques in the night-time condition are very challenging.

A CMMR technique is proposed in this research in order to solve the problem of CMMR at night. The technique presents discriminant features from available appearances. To classify the defined features, a classification strategy is also presented to recognise CMM and could possibly be used in real-world applications, such as intelligent transport, traffic law enforcement and monitoring systems.

6.1 Conclusions

The conclusions are provided as follows.

1) As shown in section 4.3.3, distinguishable features of a car rear view are introduced to recognise CMM under limited lighting conditions at night. The features of taillight and licence plate are used in the proposed method. The experimental results show that the presented features can be used to classify CMM and moreover, the average classification accuracy results are reported at more than 90%. In addition, some car models having very unique appearances are reported with high recognition accuracy with the proposed features.

2) In real video images, predefined features could be undetected due to many factors, as given in section 4.3.4. To solve this problem, the technique separates features into four feature sets depending on appearance – taillights and licence plate – detection. The numbers of each feature set are 140, 69, 131 and 65, respectively. All sets were tested in order to evaluate the robustness of the proposed technique and features used. The experimental results of each set were 93.77, 93.97, 93.56 and 93.83, respectively. The results were reported that the highest classification accuracy was the second set with 93.97%. Even though, the second set has only 69 features which is less than the first and third feature sets. From the observation, the classification accuracy does not depend on the number of features but it is greatly affected by distinguishable features used. Furthermore, using many features might lead to a number of redundant features resulting in classification error and a longer computation time. Although to classify car appearances at night has limitation, the classification accuracy of car models grained from the technique used in the present study is high, more than 90%. To consider the daytime technique, which various appearances can be used, the classification accuracy is 98% (Zhang, 2013). The classification accuracy of the car appearances at night technique is a bit lower than the daytime technique. However, with the limitation of car appearances at night, the classification

accuracy of the car appearances gained from the technique used in this study is satisfied.

3) In the research, a genetic algorithm feature subset selection technique is employed in order to find optimum (discriminant) features of each car model. As discussed in section 4.3.5, a vehicle may have a certain group of dominant features and therefore an optimum feature selection is required for application. With the implemented genetic algorithm feature selection technique, the prediction accuracy improves compared to no applied feature selection.

4) In the classification process, a binary class classification technique is applied in order to recognise the CMM of interest in an image from other models. The classification technique implements a classifier ensemble of three classifiers: Support Vector Machine, Decision Tree and k-Nearest Neighbours. Each classifier predicts test data into two classes: target and other. The final prediction is obtained by a majority vote method of the three classifiers. It has been proven elsewhere that an ensemble method can improve classification accuracy and furthermore the method can reduce data distribution (high variance) of untrained data. The proposed technique could be applied in real-world systems, for example, intelligent transport, traffic law enforcement and monitoring systems to find suspected or black-listed cars in CCTV images.

6.2 Contributions

6.2.1 CMMR technique at night

In the literature, most of previous researches present CMMR technique to be used in daytime condition that many car appearances can be easily obtained from image. This research, on the other hand, presents the first CMMR technique to solve the problem of recognition under limited light at night. Although, car appearances in image captured at night is limited, the classification accuracy of the proposed method is acceptable, more than 90% accuracy tested on 100 target car models against 400 other models.

6.2.2 Distinguishable feature used

The accuracy of CMMR relies on the discriminant car appearances or features used in image. In previous research, most of them dedicate to solve the problem of CMMR in daytime image. Variety features, for example edge feature, transform feature, texture feature, SIFT feature and SURF feature, are used as the data to recognise car make and model. At night, car appearances, texture, grill, headlight shape etc., are faded or reduced to headlight, taillight and licence plate. The daytime features and feature detection techniques used lead to incorrect CMMR in this condition. This research defined distinguishable features from available appearances to classify CMM. The accuracy from the defined features is satisfied to CMMR system implementation at night.

6.3.2 Classification strategy

In addition, the classification accuracy is depended on the classification technique. In previous studies, many classifiers and classification techniques are implemented. The research applies many classification techniques such as classification ensemble, feature selection, optimized technique and pruning method in order to have high classification accuracy as much as possible. First, classifier ensemble is employed in the research which uses more than one classifier to decide the final classification result together in order to obtain high classification accuracy. Next, feature selection is applied to select feature subset for each car model which improves the classification accuracy and can reduce computation time of classification process. Then, optimization technique is used in SVM to obtain optimum parameters in order to get high classification accuracy and last pruning technique is employed to decision tree to avoid the possibility of over-fitting in order to reduce classification error. Majority of published CMMR techniques is implemented based on multi-class classification strategy. This research presents single-class classification to classify car make and model in order to be used in real world application (traffic law enforcement) to detect car model of interest when a suspicious car model is reported.

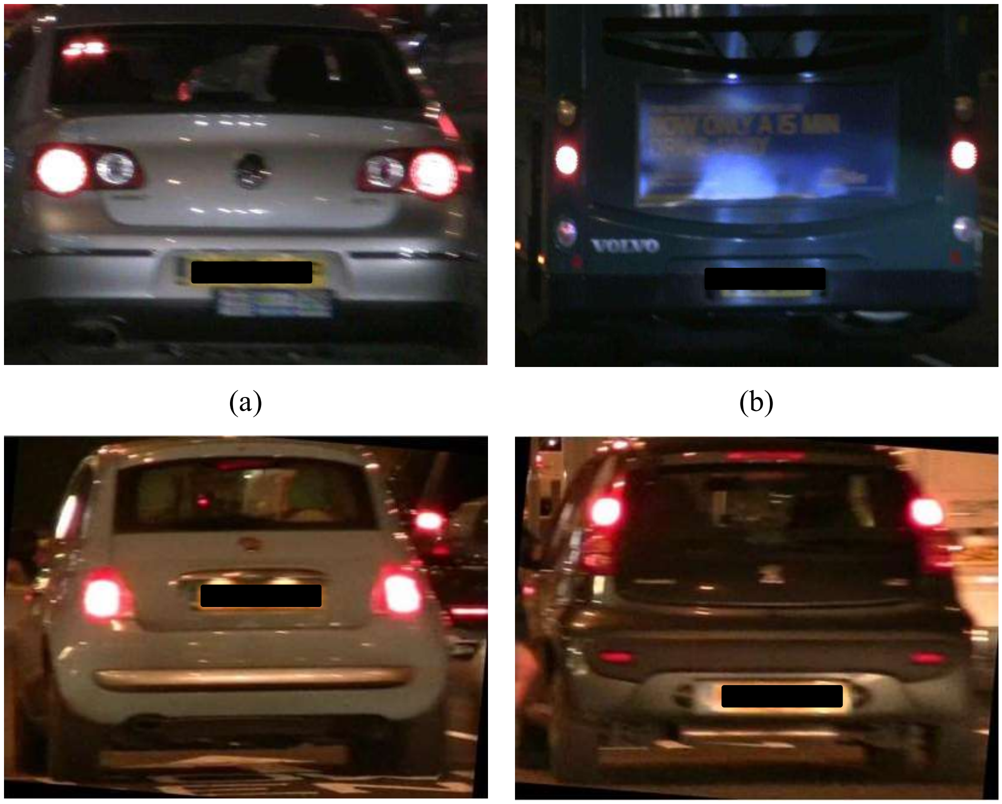
6.3 Future works

As mentioned in chapter 4, the proposed method uses taillight shape and licence plate size and position measuring as features to classify CMMs. Therefore, the limitation of this method is when those appearances are similar in many car models. This might lead to a decrease in the classification performance. First, some CMMs from the same company have similar design of visual appearances. Figure 6.1 shows car rear view of two models; Vauxhall Astra GTC and Vauxhall Astra MK6. It can be seen that their taillight shape and licence plate position are very similar.

Another problem is non-unique taillight shape, such as circular. The problem will occur when only one taillight is detected. Figure 6.2 shows example images of four cars from different companies having similar circular taillight shape. To solve this problem, increasing distinguishable features, especially taillight shape features, could present more detail of the CMM which would improve classification accuracy.

(a) (b)

Figure 6.1: Example car models with similar taillight shape from the same company. (a) Vauxhall Astra GTC. (b) Vauxhall Astra MK6.



(a) (b) (c) (d)

Figure 6.2: Example car models with similar, circular, taillight shape.
(a) Volkswagen Passat B6. (b) Volvo bus. (c) Fiat 500. (d) Peugeot 107.

Furthermore, the proposed method only considers CMMR technique under limited lighting at night where there are some lights within an image making the image not too dark. In this circumstance, the presented features can be extracted from the image that can be used to classify CMMs. However, extremely dark scenes are not mentioned in this work. In dark images, such as images captured in rural areas, few appearances may be detected such as taillights. Future work will attempt to find available dominant features to recognise CMM in this condition.

One of limitations of the current study is to rotate subject image manually until it has symmetrical view. The angles used are varied and depend on camera positions and views. Future work will attempt to find technique to rotate subject image automatically.

The study recognises car make and models only symmetrical car rear view. Therefore, images have to be rotated to the defined view before sending to the classification process. In future work, method will be able to classify car make and models from various views, for example, left side, right side and front views.

The current study can recognise only one car model at a time. Future work will improve to recognise more than one car in an image in order to use with high way or multi lanes streets.

The study uses traditional classification methods: SVM, DT, kNN and Majority voting method. Future work will attempt to implement with sophisticated or complex classification techniques, for example, convolution neural network and dynamic Bayesian network which might be able to increase classification accuracy.

The video images tested in this study were captured cars in the city area where car speed is limited (not over 50 mph). Future work will improve technique to recognise CMMs to use with unlimited car speeds.

In feature selection process, the study uses binary GA which is limited when used to select the feature subset. In order to further development, complex GA or other feature selection techniques will be used for evaluation and analysis.

The study aims to differentiate and classify targeted car model from other model. One-class classification method can be solved this problem. Future work will implement one-class classification further on this problem.

The proposed research is applied to the dataset of Chen et al. (2015). This dataset includes variety of image light conditions in daytime, various image captured angle and both front and rear view images. The results showed that the research technique cannot work well on Chen et al.(2015)'s data set because the techniques is designed to detection taillight and licence plate at night which all associative parameters are defined for specific light condition as night-time. The future work will find a technique to cope various image light conditions in both day and night-time.

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APPENDIX A

IMAGES OF TARGET CAR MODELS

VAUXHALL ASTRA MK4

VAUXHALL ASTRA MK5

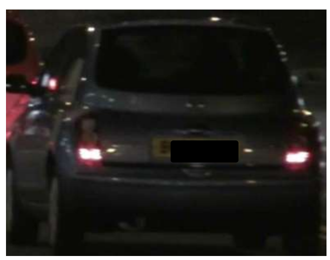
VAUXHALL ASTRA MK6

VAUXHALL CORSA C

VAUXHALL CORSA D

FORD FIESTA MK6

FORD FOCUS MK2



NISSAN MICRA K12

NISSAN QASHQAI J10

SKODA OCTAVIA 1U

TOYOTA AVENSIS T250

LONDON TAXI TX4

VAUXHALL ADAM

VOLKSWAGAN PASSAT B6

VAUXHALL ZAFIRA

VAUXAHLL VECTRA

VAUXHALL ASTRA GTC

AUDI A3 8V

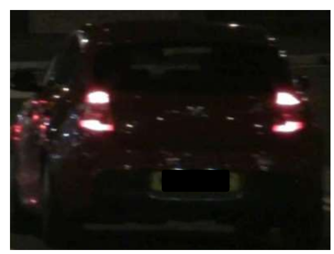
AUDI A4 B7

AUDI A1

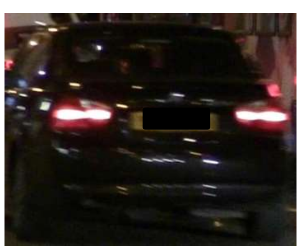
AUDI A3 8P

AUDI Q7

AUDI S5

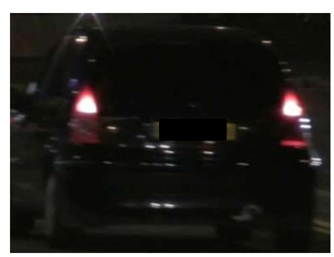


BMW 1S E87



BMW 3S E92

BMW 5S F10



CITROEN C3 1^{ST} GEN

AUDI A4 B6

CITROEN XSARA PICASSO

CITROEN C3 PICASSO

CITROEN C5 DC

VAUXHALL CORSA B

FIAT GRADE PUNTO

FIAT 500

FORD C-MAX MK1

FORD FIETA ST

FORD FIESTA MK5

FORD FOCUS MK1

FORD FOCUS ST

FORD KA

FORD MONDEO MK3

FORD TRANSIT CONNECT

HONDA CRV RD4

HONDA CRV RM1

HONDA JAZZ 1ST GEN

HONDA CIVIC MK8

LAND ROVER

MERCEDES A140

MERCEDES C-CLASS W202

MERCEDES C-CLASS W203

MERCEDES C-CLASS W204

MERCEDES E-CLASS_Coupe

MINI COUNTRYMAN

NISSAN JUKE

NISSSAN MICRA TEMPEST

PEUGEOT 206

PEUGEOT 206 GTI

PEUGEOT 207 GT

RENAULT SCENIC CONQUEST

RENAULT CLIO2

RENAULT CLIO4

RENAULT MEGANE COUPE CABRIO

RENAULT MEGANE MK2

SEAT IBIZA MK2

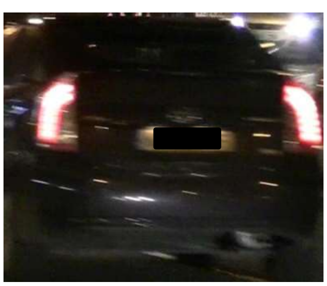
SEAT IBIZA MK3

SEAT IBIZA MK4

SEAT IBIZA MK4 ST

SKODA OCTAVIA COMBI

TOYOTA ECHO 1ST GEN



TOYOTA PRIUS 3GEN XP30

TOYOTA YARIS XP90

TOYOTA YARIS XP130

VAUXHALL INSIGNA

VAUXHALL MOKKA

VAUXAHLL TIGRA

VAUXHALL CASCADA

VOLKSWAGEN GOLF MK4

VOLKSWAGEN GOLF MK5

VOLKSWAGEN GOLF MK6

VOLKSWAGEN NEW BEETLE

VOLKSWAGEN PASSAT B5

VOLKSWAGEN PASSAT B7

VOLKSWAGEN PASSAT CC

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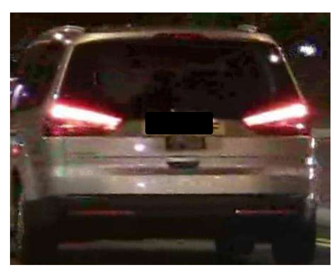
VOLKSWAGEN POLO GTI MK6

VOLKSWAGEN POLO MK4



FORD GALAXY

VOLKSWAGEN TOURAN

VOLKSWAGEN UP

VOLKSWAGEN TRANSPORT T5

AUDI S6

AUDI A3 3^{RD} GEN

BMW M5 F10

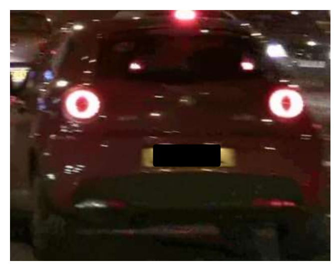
BMW 5S E60

PEUGEOT 207

TOYOTA COROLLA 9^{TH} GEN

FIAT PUNTO

TOYOTA VENZA V6



ALFA ROMEO MITO QV

AUDI A2

APPENDIX B

LIST OF CAR MODEL OPTIMUM FEATURE SUBSET

Car models	Optimum feature index	Number of features
VAUXHALL ASTRA MK4	4 5 7 8 9 10 11 14 15 16 19 22 26 28 30 31 32 36 38 40 44 45 47 56 57 61 62 63 65 67 71 72 74 78 81 82 84 88 93 94 97 101 103 108 110 111 112 113 117 118 119 120 124 125 126 134 135 136 137	59
VAUXHALL ASTRA MK5	1 2 3 5 6 8 12 13 16 20 22 24 25 27 29 30 32 34 35 37 38 41 42 43 44 45 47 51 52 55 57 58 59 66 67 71 72 73 75 79 82 88 90 92 94 95 96 100 101 102 103 104 107 113 116 117 118 120 122 125 128 130 131 133 135 136 138 140	68
VAUXHALL ASTRA MK6	2 5 7 8 10 13 17 24 26 27 28 29 30 31 37 38 39 41 46 47 54 55 57 62 64 65 68 69 71 72 74 77 79 80 83 88 90 91 92 93 94 96 104 113 114 116 118 120 121 125 130 131 135 139	54
VAUXHALL CORSA C	2 3 4 7 10 11 19 20 25 29 31 36 37 39 43 44 45 46 47 48 50 56 58 59 60 63 69 70 75 76 78 79 82 83 84 88 90 94 95 96 97 98 100 101 102 104 107 110 111 113 117 118 120 122 124 126 129	57
VAUXHALL CORSA D	4 5 6 7 8 9 11 17 18 20 22 23 24 25 26 31 32 34 37 38 39 42 44 49 50 51 55 56 57 59 62 64 65 67 68 69 70 73 74 77 78 79 84 86 88 91 93 94 95 98 99 100 101 103 104 105 107 108 109 110 114 117 118 120 122 123 125 127 128 129 131 132 133 134 136 140	76
FORD FIETA MK6	2 3 4 5 6 7 8 11 14 15 17 20 21 23 25 26 30 32 35 36 37 38 39 41 44 45 46 48 49 50 52 55 57 59 61 62 63 65 67 69 71 72 74 76 81 83 87 88 90 94 95 98 104 105 106 109 111 112 113 116 117 120 123 124 127 129 130 132 134 138	70
FORD FOCUS MK2	2 5 7 8 9 11 13 17 20 21 22 24 25 26 29 31 32 33 35 37 40 41 44 48 57 58 60 62 63 68 70 71 72 74 75 81 83 84 86 89 91 92 93 97 98 99 100 102 103 105 106 108 109 111 116 117 118 119 120 123 124 128 130 131 133 136 138 140	68

NISSAN MICRA K12	3 4 5 6 7 8 10 11 12 13 15 16 18 20 25 26 27 28 32 43 44 49 52 53 55 59 60 61 64 74 78 83 88 95 99 100 101 103 104 105 107 108 111 113 115 116 117 118 119 121 125 126 131 138 139 140	56
NISSAN QASHQAI J10	3 4 8 9 12 16 22 23 25 26 27 29 31 33 34 35 36 38 39 42 44 47 49 52 53 55 56 57 58 60 61 63 71 72 73 76 77 78 80 81 83 84 85 87 88 91 96 103 104 106 109 114 118 119 120 122 123 125 128 129 132 133 137 138 139	65
SKODA OCTAVIA 1U	1 2 5 6 10 11 13 15 17 19 20 22 24 28 31 32 34 37 38 39 40 41 43 44 46 47 48 49 51 53 56 58 61 62 63 65 67 69 70 76 77 79 84 85 88 89 91 94 97 99 103 107 110 112 114 116 117 118 121 122 127 134 135 136 139	65
TOYOTA AVENSIS T250	1 2 5 6 10 11 12 13 14 17 19 20 21 22 24 25 28 33 36 38 39 40 42 43 54 55 57 58 59 60 61 62 63 64 65 67 71 74 75 77 80 81 83 87 88 90 91 95 100 101 102 103 105 106 107 108 110 111 112 114 115 116 117 120 122 123 124 126 127 128 134 137 140	73
LONDON TAXI TX4	5 7 9 12 14 15 16 17 19 24 26 28 30 31 33 34 35 37 38 39 41 42 43 44 45 46 47 49 51 52 53 55 57 58 59 61 62 63 66 67 72 73 75 76 79 85 87 89 92 93 95 96 99 101 104 107 109 112 113 114 115 116 118 119 120 121 123 124 125 126 128 130 131 132 133 134 136 137 138	79
VAUXHALL ADAM	1 2 3 4 5 6 9 12 13 16 17 20 23 25 27 28 29 32 34 36 37 38 41 46 51 53 54 57 58 59 60 61 62 65 67 69 74 75 76 81 82 83 89 91 92 93 95 96 97 99 101 103 108 113 114 115 118 119 123 125 126 128 129 130 131 133 134 136 137 139	70
VOLKSWAGEN PASSAT B6	3 6 8 9 11 15 16 17 18 20 21 23 27 28 29 32 33 37 39 40 46 47 48 52 53 54 55 56 59 60 62 63 64 65 67 69 71 72 73 75 78 80 81 82 84 90 91 92 93 98 99 100 101 109 110 111 112 113 115 116 117 123 125 126 128 130 132 134 135 136 139	71
VAUXHALL ZAFIRA	1 2 4 6 7 8 9 10 11 16 19 20 21 22 23 26 27 28 30 32 34 36 38 41 43 44 45 50 53 55 56 59 61 63 65 66 68 71 72 73 74 75 77 81 84 86 87 89 91 92 93 97 101 103 106 108 110 111 112 114 115 119 123 124 125 127 135 137 138 140	70
VAUXHALL VECTRA	1 6 7 11 13 14 16 17 18 19 21 22 23 24 25 28 33 34 37 38 39 41 44 46 48 49 50 51 52 53 54 55 56 57 59 64 69 75 76 79 80 81 82 84 85 87 88 91 94 96 98 102 103 104 105 107 108 110 111 112 114 116 120 121 124 126 127 128 130 134 135 137 140	73
VAUXHALL ASTRA GTC	4 5 11 14 17 20 21 25 27 28 29 32 34 36 38 39 42 44 45 51 55 56 57 60 64 65 66 69 71 72 73 74 76 77 78 79 81 83 85 88 89 90 97 101 102 103 104 106 107 110 116 117 118 120 121 122 127 128 129 130 131 132 134 137 139	65

AUDI A3 8V	2 3 4 5 6 8 11 13 14 15 17 18 21 22 23 24 26 28 32 35 42 43 46 48 50 57 58 65 66 71 72 73 74 76 84 85 86 88 89 90 92 95 96 97 98 99 103 108 110 111 112 113 114 115 119 121 125 127 133 134 135 136 137 138	64
AUDI A4 B7	1 2 3 4 5 6 9 12 13 16 17 20 23 25 27 28 29 32 34 36 37 38 41 46 51 53 54 57 58 59 60 61 62 65 67 69 74 75 76 81 82 83 89 91 92 93 95 96 97 99 101 103 108 113 114 115 118 119 123 125 126 128 129 130 131 133 134 136 137 139	70
AUDI A1	1 6 9 10 12 13 15 16 18 22 23 24 25 26 30 32 34 35 36 38 39 42 43 45 46 49 51 53 54 55 60 61 62 63 64 66 67 69 71 73 74 77 78 79 82 83 84 85 91 92 93 96 101 105 108 110 115 120 121 122 123 125 127 129 132 133 135 136 137 138 139	71
AUDI A3 8P	1 2 3 5 6 8 9 10 11 12 14 16 19 23 26 27 33 34 36 40 45 48 49 50 51 54 55 58 64 65 66 68 70 71 75 78 79 80 88 90 93 96 98 99 102 103 105 106 107 109 110 112 116 117 118 119 120 121 122 128 129 130 131 135 136 137 139	67
AUDI Q7	1 2 3 5 6 10 11 15 16 18 19 21 22 23 27 29 30 31 32 34 37 38 40 41 43 44 45 49 50 53 54 55 62 66 67 69 70 71 73 74 75 76 81 83 85 86 93 98 100 101 102 103 104 105 114 115 116 117 119 124 129 138 139 140	64
AUDI S5	3 5 9 11 12 14 15 18 20 21 22 23 24 27 28 30 34 35 36 39 43 44 46 47 52 55 57 60 63 65 66 69 71 72 74 75 76 77 79 85 89 91 92 94 98 99 102 105 106 107 111 114 115 119 123 124 127 128 131 133 137	61
BMW 1S E87	1 3 6 7 10 16 25 27 33 35 39 43 44 45 46 47 48 49 51 52 57 58 60 62 64 65 66 69 71 72 74 77 79 80 82 84 85 88 89 90 92 93 96 99 103 104 105 108 109 111 117 118 119 121 123 134 139	57
BMW 3S E92	3 4 5 9 10 11 14 18 23 29 31 32 33 35 39 40 41 42 43 45 46 49 50 52 57 62 63 64 66 67 73 75 78 82 86 89 96 102 104 106 109 111 112 115 118 122 126 129 131 136 137 138 139 140	54
BMW 5S F10	1 4 6 8 10 11 13 14 17 19 21 31 32 33 34 38 44 47 49 53 55 57 65 67 70 71 73 74 75 76 79 81 85 86 87 91 94 95 99 102 107 110 114 116 119 122 123 124 125 127 128 129 130 131 134 136 138 140	58
CITROEN C3 1ST GEN	1 2 6 8 10 11 17 18 19 22 23 25 27 28 29 30 32 33 37 38 39 40 42 43 44 45 47 48 50 53 54 55 58 60 61 64 66 68 71 75 77 79 81 82 83 85 87 88 91 94 95 97 100 101 103 104 105 107 108 110 115 119 120 121 124 125 134 136	68

AUDI A4 B6	4 5 6 7 10 15 18 19 22 25 30 31 32 33 35 37 39 46 48 51 53 55 57 58 59 62 64 65 66 67 70 72 73 74 77 82 83 85 87 90 91 92 93 97 98 99 100 103 104 109 111 117 118 119 120 123 124 126 127 131 135 136 137 139 140	65
CITROEN XSARA PICASSO	1 2 7 8 10 12 13 14 15 16 20 22 23 25 28 29 31 33 34 37 38 40 42 43 45 49 58 59 64 65 66 70 73 77 79 83 85 86 89 91 93 94 95 96 98 99 100 103 106 110 115 116 117 118 121 122 125 126 129 130 132 134 135 137 139	65
CITROEN C3 PICASSO	1 2 4 5 8 9 13 16 17 19 22 23 25 29 30 32 34 36 38 40 41 46 48 49 50 51 52 54 55 56 57 58 60 62 63 65 69 73 78 82 83 86 87 89 92 93 94 97 98 100 101 103 105 106 109 113 115 117 118 119 120 121 125 127 128 130 131 133 134 140	70
CITROEN C5 DC	1 2 3 5 9 12 14 15 16 23 24 25 26 27 29 31 33 37 40 43 45 47 49 50 52 55 62 65 66 67 68 69 73 76 77 78 80 81 85 86 87 88 92 93 94 97 99 101 104 106 109 110 111 115 116 118 121 123 125 126 127 132 134 135 136 138	66
VAUXHALL CORSA B	2 3 4 6 9 10 11 13 16 17 18 23 25 26 27 28 29 32 34 38 39 41 42 47 54 55 57 58 61 63 64 65 66 69 70 77 78 79 80 81 82 87 90 95 96 97 98 102 105 106 110 112 114 118 119 121 123 129 130 132 133 135 136 137 138 139	66
FIAT GRADE PUNTO	1 3 9 11 12 13 20 22 23 25 26 27 28 32 33 34 35 36 37 39 40 41 42 45 48 50 51 53 57 59 61 62 64 69 72 73 76 82 86 89 90 92 93 95 96 100 101 102 105 110 111 113 115 120 121 123 126 128 130 132 133 134 135 136 139 140	66
FIAT 500	3 7 9 12 13 15 18 19 21 23 24 26 27 28 29 30 33 37 38 40 41 42 43 47 50 51 58 59 60 61 63 67 68 70 71 73 76 77 78 80 82 88 92 98 100 103 107 111 112 113 114 116 117 123 125 126 127 128 130 132 133 134 135 137 140	65
FORD C-MAX MK1	1 2 3 10 12 13 16 18 20 25 26 28 32 33 40 41 48 58 62 64 65 69 70 76 77 78 83 85 86 89 91 93 94 97 98 104 105 107 111 115 120 121 123 133 135 136 137 139 140	49
FORD FIETA ST	1 4 5 6 7 9 10 11 12 13 16 19 20 21 23 26 28 29 30 31 33 34 35 37 38 40 41 42 44 45 46 51 52 56 58 60 63 71 73 74 75 78 83 87 88 91 94 96 97 98 99 100 102 103 105 107 113 116 120 123 124 125 126 127 128 129 130 131 133 138 140	71
FORD FIESTA MK5	2 11 12 13 16 17 21 24 25 26 28 30 33 37 38 41 44 47 49 50 51 54 55 56 58 60 61 63 64 67 71 74 78 79 81 88 89 94 96 97 98 102 105 106 107 109 111 114 117 118 121 122 127 128 131 133 135 137 138 140	60

FORD FOCUS MK1	1 2 3 5 6 9 11 12 13 16 17 25 26 27 28 31 32 33 38 41 43 44 45 46 48 49 51 52 55 56 58 62 64 67 70 71 72 73 76 78 79 82 85 87 94 95 97 98 100 102 103 105 106 112 113 114 115 116 120 123 125 126 127 129 130 132 136 137 138 140	70
FORD FOCUS ST	2 3 4 6 11 12 14 16 18 19 21 23 24 27 28 29 32 34 36 39 40 45 48 49 50 51 54 55 56 57 59 60 61 62 65 66 69 72 76 77 78 79 83 84 85 86 87 91 92 93 94 95 96 97 99 101 104 107 109 110 112 113 114 115 117 119 123 125 126 128 129 130 138 140	74
FORD KA	2 4 15 21 22 27 30 31 33 35 36 37 39 42 44 45 46 47 48 49 50 52 57 65 66 70 72 74 75 76 81 85 87 88 89 94 96 97 99 101 106 107 109 110 111 112 113 115 116 117 118 119 120 121 123 124 126 133 140	59
FORD MONDEO MK3	4 5 6 7 9 15 16 17 19 23 24 27 28 32 34 46 47 48 49 50 52 53 54 57 59 60 61 64 66 67 68 70 74 75 77 78 79 84 85 86 88 90 92 94 98 99 101 105 106 107 108 109 110 113 114 116 118 119 121 125 126 128 129 131 132 134 135 137 138 140	70
FORD TRANSIT CONNECT	2 3 7 8 11 16 20 21 22 23 24 25 28 30 32 33 34 40 47 49 51 56 57 61 62 64 68 69 71 73 74 76 77 79 80 82 85 94 96 97 99 102 108 109 110 111 113 115 122 123 124 125 126 127 130 133 136 137 138 139 140	61
HONDA CRV RD4	1 2 3 4 6 9 11 12 15 17 20 22 23 24 25 26 28 30 31 32 33 34 35 36 37 38 39 41 42 43 44 45 47 48 49 50 52 54 55 56 57 58 59 61 62 63 65 69 72 74 76 78 80 82 83 84 85 86 88 89 91 92 93 94 97 98 99 101 102 103 104 105 106 108 111 112 114 120 121 122 123 125 129 132 134 137 139	87
HONDA CRV RM1	1 2 3 8 10 15 16 21 26 28 29 31 33 34 35 36 38 39 41 45 46 49 51 54 55 56 58 59 62 64 66 70 71 73 74 77 79 80 85 88 90 94 95 96 101 102 104 107 109 111 112 114 115 116 119 122 124 126 129 131 133 136 137 139	64
HONDA JAZZ 1ST GEN	2 7 9 10 12 13 14 15 16 17 21 23 25 31 33 34 35 36 37 39 43 45 46 47 48 54 55 56 58 60 61 65 67 70 81 82 83 84 85 88 91 95 96 97 98 99 101 102 107 108 110 113 117 118 119 120 123 126 128 131 133 135 140	63
HONDA CIVIC MK8	1 2 3 4 6 10 11 15 23 24 32 33 44 46 50 51 54 55 59 60 65 67 69 70 71 74 75 76 77 78 79 81 83 87 88 89 91 94 96 100 102 104 107 117 120 122 125 130 131 138 139	51
LAND ROVER RANGE ROVER	1 3 6 7 8 10 12 17 20 21 22 23 26 28 29 30 31 32 34 37 39 40 46 48 49 50 51 54 56 57 60 61 62 65 66 68 70 73 74 75 82 86 87 92 94 96 97 99 100 101 104 107 110 111 112 113 115 118 120 125 130 132 133 134 135 137 139 140	68

MERCEDES A140	1 2 3 5 6 7 9 14 15 18 21 22 23 24 36 37 39 41 42 43 45 46 48 51 52 54 55 57 59 61 62 63 69 74 76 78 82 86 89 90 92 94 96 97 98 101 102 103 104 105 106 108 109 110 112 113 116 117 118 120 122 123 126 128 129 131 133 134	68
MERCEDES C-CLASS W202	3 6 11 13 14 15 18 19 21 22 23 24 25 27 30 31 32 34 37 39 40 41 43 46 49 50 54 55 57 58 62 64 66 68 70 71 75 78 79 89 91 92 94 95 96 97 100 104 105 106 108 109 112 114 115 117 119 120 121 123 125 129 131 133 138 139	66
MERCEDES C-CLASS W203	2 3 4 6 13 14 15 17 19 21 26 29 33 34 38 39 44 46 47 48 49 50 52 54 59 62 63 67 69 73 75 76 83 84 85 86 90 91 92 93 96 97 99 100 102 103 105 106 107 109 111 113 121 122 123 124 127 131 133 135 136 137	62
MERCEDES C-CLASS W204	7 9 11 17 19 21 22 23 25 28 30 33 35 37 40 42 43 44 45 46 55 56 59 62 64 65 66 67 68 69 70 77 78 79 82 84 89 90 92 95 96 98 100 104 107 111 116 117 118 119 120 121 122 124 128 131 138 139 140	59
MERCEDES E-CLASS COUPE	2 4 6 8 10 11 16 21 22 23 26 27 30 33 35 42 46 50 53 55 56 62 63 66 67 68 70 75 82 83 86 91 93 100 101 107 111 112 114 117 118 120 121 125 129 132 134 136 140	49
MINI COUNTRYMAN	1 3 9 10 13 18 19 21 23 24 26 30 33 36 39 41 42 45 47 48 49 50 53 55 57 59 60 63 71 73 75 77 81 82 84 87 89 90 99 102 103 106 108 112 113 115 116 118 119 120 122 123 124	53
NISSAN JUKE	2 4 5 6 7 10 13 16 17 19 20 26 29 32 33 34 36 38 39 41 49 52 55 56 57 58 59 65 66 69 71 74 76 78 82 84 88 89 93 94 95 96 99 100 102 105 109 110 112 113 114 116 117	53
NISSSAN MICRA TEMPEST	1 6 7 9 10 15 16 18 19 20 23 24 25 26 30 31 33 38 43 45 46 47 51 52 53 56 57 58 61 70 73 74 78 80 83 85 92 93 97 99 100 104 106 107 112 115 117 119 120 121 122 125 129	53
PEUGEOT 206	2 3 4 5 6 7 9 14 15 17 19 21 23 28 29 31 35 36 37 38 40 44 47 48 49 51 53 54 55 58 60 61 62 64 66 67 68 70 72 78 79 86 88 89 94 95 96 99 102 103 104 106 107	53
PEUGEOT 206 GTI	3 9 10 11 12 13 14 16 17 19 20 26 28 29 32 34 35 37 39 40 41 42 44 45 46 47 50 55 56 57 58 61 63 66 67 68 69 72 74 77 78 81 82 83 86 87 88 90 91 93 95 96 101	53
PEUGEOT 207 GT	1 2 7 8 9 16 17 18 21 22 26 28 32 33 39 41 45 47 48 54 56 60 63 64 67 70 74 77 81 82 87 88 89 91 92 93 94 95 97 101 102 103 104 106 108 110 112 118 128 129 131 137	52

RENAULT SCENIC CONQUEST	2 4 9 11 12 13 15 16 17 18 19 22 23 26 27 30 32 33 35 36 39 40 41 43 44 46 49 56 57 58 60 62 64 65 68 70 72 77 81 83 95 97 98 99 102 103 104 108 111 112 113 119 120 122 124 127 128 129 136 137 139	61
RENAULT CLIO2	2 3 5 6 7 8 15 17 18 19 21 25 27 28 29 36 39 41 42 43 47 50 51 52 54 55 56 60 63 64 66 67 73 75 77 82 87 89 90 91 93 94 95 96 97 99 103 104 108 113 114 118 119 120 121 123 125 127 129 134 137 138 139 140	64
RENAULT CLIO4	1 6 9 13 18 19 20 21 23 24 26 27 28 31 32 36 40 41 42 44 47 48 54 55 56 57 59 62 64 65 67 69 70 73 74 76 77 78 82 83 85 86 87 89 90 91 92 93 96 97 99 100 101 102 103 104 106 107 109 111 114 115 116 118 119	65
RENAULT MEGANE COUPE CABRIO	3 5 7 10 14 15 16 18 20 22 26 28 29 30 31 35 36 37 39 41 42 44 45 46 47 48 50 52 53 54 55 57 59 60 65 68 70 71 76 78 79 84 88 91 92 94 95 96 97 98 106 107 108 115 117 119 120 121 122 124 126 129 131 132 133 136 140	67
RENAULT MEGANE MK2	2 4 6 8 9 10 12 13 16 17 20 25 26 28 32 34 36 37 38 40 44 46 48 50 51 52 54 55 56 57 58 60 61 63 64 65 66 67 72 73 76 78 81 84 85 92 100 101 102 104 105 108 109 110 111 112 114 115 116 118 119 120 122 129 135 137 138 139 140	69
SEAT IBIZA MK2	1 5 7 8 9 11 17 18 24 25 27 29 30 31 34 36 40 43 44 46 49 50 51 53 55 56 64 67 68 69 72 73 74 75 76 78 82 90 94 96 99 101 102 103 104 105 106 109 110 113 117 118 121 122 124 127 128 130 131 132 133 134 135 136 137 138 139	67
SEAT IBIZA MK3	4 7 9 12 14 16 18 22 23 24 30 31 34 35 36 38 39 40 42 43 44 48 52 54 55 56 58 59 60 65 67 68 70 71 72 74 77 78 81 82 84 85 87 88 89 90 92 93 97 98 102 105 108 111 112 115 116 119 121 123 128 129 130 134 135 138	66
SEAT IBIZA MK4	2 4 8 15 17 20 21 22 23 25 28 30 32 34 35 36 39 40 42 50 57 58 59 68 71 72 73 75 76 79 80 82 87 94 95 96 99 100 105 106 107 108 109 111 113 115 119 121 123 124 125 128 129 133 134 135	56
SEAT IBIZA MK4 ST	1 2 3 5 8 11 13 16 17 18 19 20 21 22 24 26 28 30 31 32 35 36 37 39 45 46 49 50 57 58 59 62 63 65 66 68 69 70 72 73 74 75 76 78 79 82 83 84 85 86 89 91 94 97 98 100 105 106 108 109 114 115 116 117 118 119 120 123 125 127 129 134 138	73
SKODA OCTAVIA COMBI	2 4 5 6 8 14 15 16 19 22 23 25 29 32 35 36 44 46 50 52 53 54 55 61 66 67 75 82 83 84 86 88 90 93 100 101 102 103 110 115 118 119 121 126 128 129 131 133 138 139	50

TOYOTA ECHO 1ST GEN	1 2 6 8 9 10 17 20 24 25 26 28 30 31 32 34 35 38 39 42 43 44 45 46 48 49 52 53 54 55 61 64 65 71 76 77 79 80 83 85 89 91 94 95 96 99 100 101 104 109 111 112 114 117 118 119 121 123 128 130 131 132 135	63
TOYOTA PRIUS 3TH GEN XP30	2 3 4 7 8 9 11 12 14 18 19 23 24 25 31 34 35 36 37 40 42 43 46 47 48 53 54 55 57 58 61 62 64 66 67 73 74 75 78 79 81 82 85 87 88 97 98 100 102 103 107 110 112 115 119 121 123 126 129 131 132 134 135 137 138 139 140	67
TOYOTA YARIS XP90	3 6 7 8 11 12 13 15 18 19 20 22 23 26 28 30 31 32 38 39 40 41 44 45 49 51 53 58 59 66 69 72 79 83 85 87 88 91 93 96 97 98 99 101 105 106 107 110 112 117 118 120 123 124 125 130 131 132 133 135 139	61
TOYOTA YARIS XP130	1 2 9 10 12 14 16 19 20 21 22 26 28 31 32 35 36 37 38 39 41 45 47 49 50 51 52 53 55 56 57 62 65 66 72 74 75 76 78 79 80 82 83 84 87 88 89 92 98 99 100 101 102 103 104 105 106 116 118 119 122 123 126 127 129 130 131 132 137	69
VAUXHALL INSIGNA	2 3 5 15 16 22 24 25 27 29 30 31 33 38 39 40 46 47 51 52 55 62 66 67 68 71 72 75 76 77 79 82 84 86 88 89 90 92 94 98 100 102 103 106 107 111 117 119 120 121 126 127 128 131 138 139 140	57
VAUXHALL MOKKA	2 3 4 6 10 12 16 18 20 23 25 26 30 32 33 37 38 39 41 43 44 45 46 48 56 57 59 60 61 64 67 69 74 75 79 84 85 86 93 94 97 102 103 105 106 107 109 112 114 115 121 123 124 126 127 130 135 138 140	59
VAUXAHLL TIGRA	2 3 5 6 7 8 11 12 14 15 18 19 24 26 27 28 30 35 37 42 44 45 47 49 51 54 58 59 60 61 63 64 65 72 73 74 79 81 85 86 88 89 90 91 93 95 96 97 98 103 105 107 108 109 111 112 116 118 123 124 126 127 129 130 131 136 137 140	68
VAUXHALL CASCADA	1 2 3 5 7 11 15 16 22 28 29 30 34 40 41 43 45 46 48 53 55 59 68 70 71 74 82 83 85 88 90 92 95 96 103 104 106 108 110 111 112 113 114 118 119 120 123 126 127 128 129 133 135 136 138	55
VOLKSWAGEN GOLF MK4	2 4 6 8 9 10 11 14 16 18 22 24 25 27 28 30 31 32 33 35 36 38 39 42 43 47 49 50 51 53 60 61 63 64 65 66 74 75 80 81 82 86 88 91 92 93 95 96 99 102 104 105 106 107 109 110 114 115 119 121 122 124 125 127 130 136	66
VOLKSWAGEN GOLF MK5	3 4 6 8 11 13 14 15 16 17 22 23 24 25 27 28 29 30 31 32 34 38 40 41 47 48 49 51 52 54 55 60 62 63 64 65 66 67 72 73 76 77 79 80 82 87 88 89 90 94 99 102 105 110 112 113 115 122 123 124 127 129 130 132 135	65
VOLKSWAGEN GOLF MK6	1 6 7 9 11 13 15 16 17 20 23 31 32 39 40 41 42 46 47 49 53 55 56 64 66 67 68 69 73 76 79 82 87 88 89 91 92 93 95 98 99 100 101 102 106 112 113 114 116 117 118 126 127 129 130 133 139	57

VOLKSWAGEN NEW BEETLE	1 2 3 5 6 10 11 12 14 15 19 20 24 26 29 33 34 37 38 39 40 41 42 46 47 49 52 53 55 56 59 60 63 64 66 67 70 72 75 76 79 80 83 87 88 89 91 93 95 96 99 101 104 105 106 108 109 112 113 115 116 117 118 119 120 121 122 125 126 128	70
VOLKSWAGEN PASSAT B5	1 3 5 7 9 10 20 21 23 24 31 32 33 34 40 43 44 45 48 53 59 60 63 64 65 67 76 79 80 82 83 85 87 90 94 96 97 99 102 105 106 108 110 111 114 115 117 119 120 124 125 126 131 137 139	55
VOLKSWAGEN PASSAT B7	1 3 4 6 9 11 13 15 16 19 20 24 25 27 35 36 39 44 48 49 51 54 55 56 59 61 65 67 71 75 77 79 82 83 84 86 87 88 90 94 96 97 99 100 107 108 115 117 118 119 120 124 125 127 136 137 139 140	58
VOLKSWAGEN PASSAT CC	2 3 5 6 8 9 10 14 15 16 17 19 22 23 24 25 27 30 33 34 36 37 39 48 49 51 52 54 56 58 60 61 62 63 65 67 72 73 75 76 80 81 83 86 87 89 92 93 94 96 100 101 103 106 108 110 114 118 119 123 124 127 130 131 133 134 136 137 140	69
VOLKSWAGEN POLO GTI MK4	1 4 5 8 9 10 14 17 18 21 22 26 27 31 38 47 49 50 51 54 56 60 61 62 66 67 72 73 74 75 77 82 84 87 88 91 92 93 95 97 98 101 102 103 106 107 108 109 111 114 115 119 121 123 124 125 126 127 128 129 130 131 133 134 135 136 138 139 140	69
VOLKSWAGEN POLO GTI MK6	1 2 4 8 9 10 12 14 16 17 18 21 23 24 25 26 27 28 29 30 31 33 38 41 42 44 45 51 54 57 59 62 64 73 75 77 85 94 95 100 108 109 115 118 122 123 125 127 129 130 131 132 133 135 137 138 139 140	58
VOLKSWAGEN POLO MK4	5 11 12 15 16 17 25 29 31 33 36 37 41 45 46 47 49 52 53 54 57 58 59 63 64 66 68 69 71 75 77 78 79 80 83 84 85 88 90 92 93 94 98 99 103 104 105 106 109 111 114 115 120 121 122 124 126 129 134 135 136 138 140	63
FORD GALAXY	3 5 8 9 10 13 15 21 22 25 28 30 32 33 34 37 39 46 47 48 50 51 53 54 57 58 61 62 63 64 68 69 70 72 74 78 79 80 81 88 89 90 91 96 98 99 108 109 110 111 112 117 118 119 122 123 128 129 131 132 135 138	62
VOLKSWAGEN TOURAN	1 3 4 5 6 7 9 10 14 15 17 18 19 24 25 26 29 35 36 37 39 41 42 43 45 46 47 49 50 51 52 54 58 64 66 70 71 73 82 92 95 98 103 106 109 110 111 114 116 121 123 125 126 131 132 133 135 136 137 138 139 140	62
VOLKSWAGEN UP	3 6 9 13 14 16 17 19 22 27 28 29 35 38 40 42 43 44 46 47 48 50 51 52 58 59 63 64 65 67 70 72 73 74 75 78 81 82 86 91 94 97 98 99 100 101 102 103 105 109 113 114 116 117 125 126 128 129 131 132 133 134 135 136 138 139 140	67

VOLKSWAGEN TRANSPORT T5	1 2 4 5 6 8 12 15 21 26 27 28 29 31 34 38 39 40 41 45 46 47 48 51 52 53 55 56 57 59 60 65 66 67 77 78 79 81 84 85 89 91 95 96 97 98 104 108 112 113 115 117 118 121 124 125 127 131 132 139	60
AUDI S6	2 4 5 6 12 14 15 16 17 19 20 22 23 24 26 27 34 37 38 39 41 42 46 47 49 50 51 52 56 58 62 63 64 66 73 74 77 83 88 89 90 91 95 96 98 99 100 101 102 103 110 113 116 118 120 122 124 128 129 131 135 136 140	63
AUDI A3 3RD GEN	5 7 10 11 12 18 19 20 26 32 33 34 36 37 41 42 43 47 48 49 51 55 57 58 59 61 62 64 65 68 71 73 76 80 82 83 84 90 93 94 96 97 98 99 100 101 102 103 105 107 109 112 113 114 117 118 119 123 129 130 133 134 135 136 139 140	66
BMW M5 F10	2 4 7 8 10 12 13 14 16 17 19 23 24 25 26 27 28 29 30 31 33 36 37 39 40 41 44 46 48 49 51 56 58 60 61 62 64 66 69 73 76 78 85 88 89 90 91 97 99 101 111 113 114 117 119 122 126 127 129 131 135 136 139	63
BMW 5S E60	2 4 5 7 8 9 10 15 18 21 23 24 26 27 28 30 31 32 36 38 39 40 41 42 43 44 47 48 49 51 53 55 57 59 60 67 68 69 72 73 74 78 79 83 87 90 91 92 93 95 96 98 99 100 106 107 111 112 115 116 118 120 123 124 125 128 129 131 135 136 137 139	72
PEUGEOT 207	2 5 10 11 12 15 17 19 20 21 25 27 28 29 31 35 37 41 44 45 46 47 49 52 53 54 55 56 57 59 60 62 63 65 67 70 74 76 78 80 87 90 92 95 99 104 105 109 110 112 114 118 119 120 124 127 128 129 134 135 136 137 138 139	64
TOYOTA COROLLA 9TH GEN	1 2 7 8 11 13 14 15 16 18 24 26 27 28 29 32 33 34 35 36 42 47 48 49 51 54 55 56 57 59 61 63 65 66 67 69 70 72 73 74 77 78 79 80 83 88 89 90 91 92 94 96 97 99 103 105 106 107 108 110 111 115 116 119 120 123 124 125 126 130 137 140	72

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TOYOTA VENZA V6	1 2 3 4 5 6 8 9 10 11 12 13 19 20 21 25 27 28 29 30 31 35 37 39 40 44 48 52 53 59 61 62 63 64 65 66 67 69 74 75 76 79 81 82 83 87 88 89 90 91 92 94 95 96 98 100 101 103 104 106 111 113 114 115 116 117 119 122 123 129 132 134 135 137 138 139	76
ALFA ROMEO MITO QV	3 5 7 12 13 15 17 19 20 21 22 24 26 28 29 30 31 32 33 34 35 37 41 42 43 44 46 48 49 52 55 56 61 62 64 66 68 69 72 74 77 78 83 84 85 86 87 88 90 91 92 96 98 99 101 104 105 110 111 114 116 118 119 122 123 125 127 130 133 134 135 136 139	73
AUDI A2	2 3 6 7 9 12 13 16 17 19 22 23 24 25 26 28 29 30 31 32 35 37 38 42 47 55 56 57 58 60 61 64 65 67 70 71 73 74 76 77 78 79 80 84 86 87 90 91 92 93 95 98 99 100 101 102 105 106 113 115 116 117 119 121 125 127 128 132 134 135 136 137 139	73

APPENDIX C
PUBLICATIONS

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